MEASURING THE EFFECT OF UNCERTAINTY IN UNIT COST AND PRE-TREATMENT CONDITION ON PAVEMENT MAINTENANCE AND REHABILITATION DECISIONS

A Thesis

by

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ABSTRACT

A pavement maintenance and rehabilitation (M&R) project normally extends over 2-10 mile long roadway segment. At the M&R planning stage, these projects are called pavement management sections, which are often comprised of multiple data collection sections. The fact that a management section is comprised of multiple data collection sections introduces variability into the condition of the pavement within each M&R project. Also, variability is often found in the cost of M&R projects of the same M&R type. These variability are poorly understood and qualified in the pavement management literature. Accounting for these uncertainties in pre-treatment pavement condition and in the M&R treatment cost is essential for obtaining realistic estimate of needed funding. This research addresses this knowledge gap by a) developing probability density functions for pavement pre-treatment condition indicators and M&R unit cost, and b) developing a novel probabilistic methodology for estimating M&R funding needs for pavement networks that accounts for these uncertainties.

Data was obtained from the Bryan district pavement management plan for 2012 and from the Texas Department of Transportation (TxDOT) Pavement Management Information System (PMIS). Probability distribution functions were fitted for distress score, ride score, and unit cost using the @Risk software. Also, a simplified decision tree was developed to help simulate the maintenance and rehabilitation treatment selection process. This decision tree considers ride score, distress score, and traffic volume. After fitting the probability distributions of pavement condition indicators and unit cost, the

impact of uncertainty in them on funding needs estimate was investigated using Monte Carlo simulation, The analysis shows that the needs estimate produced by TxDOT for the studied projects falls within the 90 percent confidence interval of the simulated need estimate.

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NOMENCLATURE

ACP	Asphalt Concrete Pavement
A-D	Anderson-Darling
ADT	Average Daily Traffic
AIC	Akaike Information Criterion
BRMN	Beginning Reference Marker Number
BIC	Bayesian Information Criterion
CRCP	Continuously Reinforced Concrete Pavement
DS	Distress Score
ERMN	Ending Reference Marker Number
HR	Heavy Rehabilitation
IRI	International Roughness Index
JCP	Jointed Concrete Pavement
K-S	Kolmogorov-Smirnov
LCCA	Life-Cycle Cost Analysis
LMDP	Latent Markov Decision Process
LR	Light Rehabilitation
MR	Medium Rehabilitation
M&R	Maintenance and Rehabilitation
MU	Maintenance Unit
NN	Needs Nothing

PM	Preventive Maintenance
PMP	Pavement Management Plan
PMS	Pavement Management System
PMIS	Pavement Management Information System
RM	Routine Maintenance
RS	Ride Score
SI	Serviceability Index
TxDOT	Texas Department of Transportation

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1. INTRODUCTION

1.1 Background

The increasing shift from new construction of highways to maintenance and rehabilitation (M&R) of existing systems combined with limited funds motivated highway agencies to seek improved pavement management systems (PMS) for identifying cost-effective M&R treatments at both the project and network levels (Finn et al. 1990). Network-level analysis tools are used to support planning and programming decisions for the entire roadway network. Project-level analysis tools support the evaluation of alternative treatments for a specific roadway segment and the design of the M&R projects included in the work program (Dessouky et al. 2011).

An M&R project normally extends over 2-10 mile long roadway segment. At the M&R planning stage, these projects are called pavement management sections. A management section is defined as a section of pavement of similar structure that engineers intends to maintain in a uniform manner (TxDOT's PMIS Technical Manual, 2011). However, pavement data is often collected and stored for sections that are a fraction of a mile in length (e.g., 0.1 mi, 0.5 mi).

The Pavement Management Information System (PMIS) of the Texas Department of Transportation (TxDOT), for example, contains valuable data such as pavement inventory, condition, and traffic for data collection sections that are typically

0.5 mile in length. Thus a management section (and ultimately an M&R project) is often comprised of multiple data collection sections.

The fact that a management section is comprised of multiple data collection sections introduces variability into the condition of the pavement within each M&R project. Also, variability is often found in the unit cost of similar M&R projects (e.g., same treatment type). These variability are poorly understood and quantified in the pavement management literature. Accounting for variability in pavement condition within M&R projects and in the cost of M&R treatment is essential for obtaining realistic estimates of needed funding and identifying candidate M&R projects under limited funding scenarios.

1.2 Problem Statement

Highway agencies develop pavement management plans (PMPs) that identify candidate M&R projects, including M&R treatment type, project limits, and estimated costs. In Texas, each district of TxDOT is required to develop a four-year pavement management plan. Pavement condition is a major factor in determining what management sections should receive M&R treatment, what type of M&R treatment should be applied, and when the treatment should be applied under the reality of limited budget. Variability in pavement condition within each management section introduces uncertainty into pavement management plans. Traditionally, this uncertainty is often ignored. For example, input variables are treated as discrete fixed values, as if the values are certain. This method does not consider the variance of pavement condition indicators within each management section and it may exclude information that could improve the pavement management decision making process. In other words, the result of this method reflects the “average” state of all data collection sections rather than the true condition of the pavement management section.

A similar limitation is that most PMIS use average unit cost for M&R treatment types in the development of pavement management plans and needs estimates. The unit cost for each M&R treatment type includes material-related costs and construction-related costs such as labor cost, equipment cost, and traffic control cost. Variability in these costs introduces uncertainty into the unit cost of each treatment type. Normally, pavement M&R treatment types include preventive maintenance (PM), light rehabilitation (LR), medium rehabilitation (MR), and heavy rehabilitation (HR).

In this research, a pavement condition probability distribution will be fitted for each management section planned to receive M&R treatment. Similarly, instead of simplistically using the average unit cost of each M&R treatment to calculate total M&R cost, the distribution of unit cost for each M&R type are developed. By using the distributions of pavement condition and unit cost for each M&R treatment, it is possible to estimate a distribution for the total needed budget to preserve the entire pavement network for any given level of confidence. Ultimately, quantifying the variability in pavement condition and M&R costs will help advance pavement management methods from deterministic approaches to more realistic probabilistic approaches.

1.3 Research Objective

The goal of this research is twofold: a) to measure the uncertainty in the field characteristic of pavement M&R projects, specifically pavement condition and cost, and b) develop a probabilistic methodology for estimating M&R funding needs for pavement networks that accounts for these uncertainties. The specific objectives of this research are to:

1) Fit the probability distribution of pavement condition indicators for pavement management sections planned for M&R;
2) Fit the probability distribution of unit costs for M&R treatment categories;
3) Build a simplified decision tree to simulate the M&R treatment selection process;
4) Investigate the impact of variability in pavement condition and cost on pavement management decisions at the network-level.

1.4 Research Tasks

To accomplish the objectives of this research, the following tasks have been completed:

- Task 1 : Review of Related Literatures

  The literature on pavement M&R planning and programming was reviewed to understand the essential factors commonly used in pavement decision tree and the process of M&R project development. Studies on estimating pavement condition state for needs analysis and PMP development were given specific attention to understand the current methods and practices. Also, simulation methods pertinent to infrastructure management have been reviewed to help identify appropriate techniques for analyzing and modeling variability in unit cost and pavement condition.

- Task 2 : Obtain and Organize Data

  This research effort uses data obtained from TxDOT's Pavement Management Information System (PMIS) database and the 2012-2015 PMP for the Bryan district. Data on pavement pre-treatment condition, traffic volume, and number of lanes was obtained from the PMIS. Data on M&R project limits, M&R type, and M&R cost was obtained from the 2012-2015 PMP. The two datasets were matched and merged to form a common dataset for use in this research.

- Tasks 3: Fit Probability Distributions to M&R Unit Cost and Pavement Condition Indicators.

  Unit cost ($/lane-mile) was computed for each M&R project listed in the 2012-2015 PMP. These unit costs were then analyzed for each M&R treatment category to identify the best-fit probability distribution. Also, probability distributions for pre-treatment distress score and ride score were fitted for each M&R project considered in this study.

- Task 4: Develop a Simplified Decision Tree

A simplified decision tree was developed based on reviewing TxDOT's existing decision trees and current practices at highway agencies. The developed decision tress considers three major factors (traffic volume, ride quality, and surface condition). The output of this decision tree is a treatment type (preventive maintenance or rehabilitation) or "do nothing." This decision tree is then used to simulate the process of selecting an M&R action for each pavement management section.

- Task 5: Simulate the Impact of Uncertainty in M&R Cost and Pre-Treatment Condition on Pavement Management Decisions

  The impact of uncertainty in unit cost and pre-treatment condition on pavement management decisions at the network-level (e.g., needs estimate) was investigated through Monte Carlo simulation.

1.5 Thesis Organization

This thesis is divided into eight sections, as described next.

Section 1 describes the research problem, research objectives, and the approach used to meet these objectives.

Section 2 provides a review of existing literature on research topics relevant to this thesis, including needs estimates for pavement networks, decision trees for M&R of asphalt concrete pavement, and Monte Carlo simulation.

Section 3 describes the approach used for matching the PMIS data collection sections to PMP projects based on highway location information. Also, this section describes the methods used for aggregating inventory data, condition data, and construction data each PMP project. Finally, the new database that was used in this research to run the simulation process is described.

Section 4 fits probability distributions for distress score, ride score, and unit cost using the @Risk software.

Section 5 describes the process that was used for developing the simplified decision tree.

Section 6 assesses the impact of uncertainty in unit cost and pre-treatment condition of M&R projects on budget need estimates and pavement condition using Monte Carlo simulation.

Section 7 summarizes the research effort provides conclusions.

Section 8 offers recommendations for future work.

2. LITERATURE REVIEW

2.1 Pavement Management Process

The American Association of State Highway and Transportation Officials (AASHTO) defines pavement management as “the effective and efficient directing of the various activities involved in providing and sustaining pavements in a condition acceptable to the traveling public at the least life cycle cost (AASHOT 1985).” Pavement management is the process through which agencies collect and analyze data about roadway systems and make decisions on the maintenance, repair and reconstruction applications over a planning horizon (Haas et al. 1994; Finn 1998). To help improve pavement management activities, Pavement Management Systems (PMPs) are used by most state department of transportation. The process for developing a PMS is usually conducted in the following six steps (Peng and Ouyang, 2010):

- Determine pavement condition indices
- Develop performance prediction model
- Define treatment alternatives
- Build decision tree for triggering M&R
- Determine M&R trigger criteria
- Develop project prioritization approach

The Texas Department of Transportation (TxDOT) uses TxDOT’s Pavement Management Information System (PMIS), which includes a series of analysis programs as a set of tools that can assist decision-makers in finding cost-effective strategies for providing, evaluating, maintaining and rehabilitating pavements in a good serviceable condition (TxDOT's PMIS Technical Manual, 2011). These analysis programs are:

- Needs Estimate: Based on condition assessment data and network inventory data to estimate pavement preventive maintenance and rehabilitation needs (lane miles and dollars) for past, present, and future Fiscal Years;
- Projected Pavement Condition: Forecasts the condition of a pavement section one or more years into the future and estimates the treatment (and cost) that will be needed if no work is done beforehand;
- Optimization: Prioritize pavement sections for M&R in current and future Fiscal Years to yield the greatest cost effectiveness within funding limits;
- Impact Analysis: Determines the impact of pavement funding, truck traffic changes and preventive maintenance seal coat practices on pavement condition for current and future fiscal years.

2.2 M&R Treatment Selection Tools

The major objectives of a network-level pavement management system are to develop short-term and long-term budget need estimates and to produce a list of potential projects based on a limited budget. The optimum approach to achieve these objectives relies heavily on the prediction of pavement performance and life-cycle cost analysis of all feasible maintenance and rehabilitation strategies (Butt et al. 1994).

- Pavement surface type and/or construction history
- An indicator of the functional classification and/or traffic level

- At least one type of condition index, including distress and/or roughness
- Specific information about the type of deterioration present, either in terms of an amount of load-related deterioration or the presence of a particular distress type
- Geometrics, in order to indicate whether pavement widening or shoulder repair should also be required
- Environmental conditions in which the treatment is to be used

Hicks et al. (2000) defined the decision tree as a tool that incorporates a set of criteria for identifying a particular treatment through the use of "branches." Each branch represents a specific set of conditions (in terms of factors such as pavement type, distress type and level, traffic volume, and functional classification) that ultimately leads to the selection of a particular treatment. The Network Level Concrete Decision Tree used in Minnesota DOT is shown as an example in Figure 2.1.

Decision Matrices are structurally similar to the decision trees as they also rely on a set of criteria to select an appropriate maintenance or rehabilitation treatment for a given pavement. However, the major difference is that decision trees provide a more graphical approach to the selection process while decision matrices provide tabular forms that makes them are able to store more information in a smaller space (Hicks et al., 2000). Nebraska Flexible Pavement Maintenance Decision Matrix is shown as an example in Table 2.1

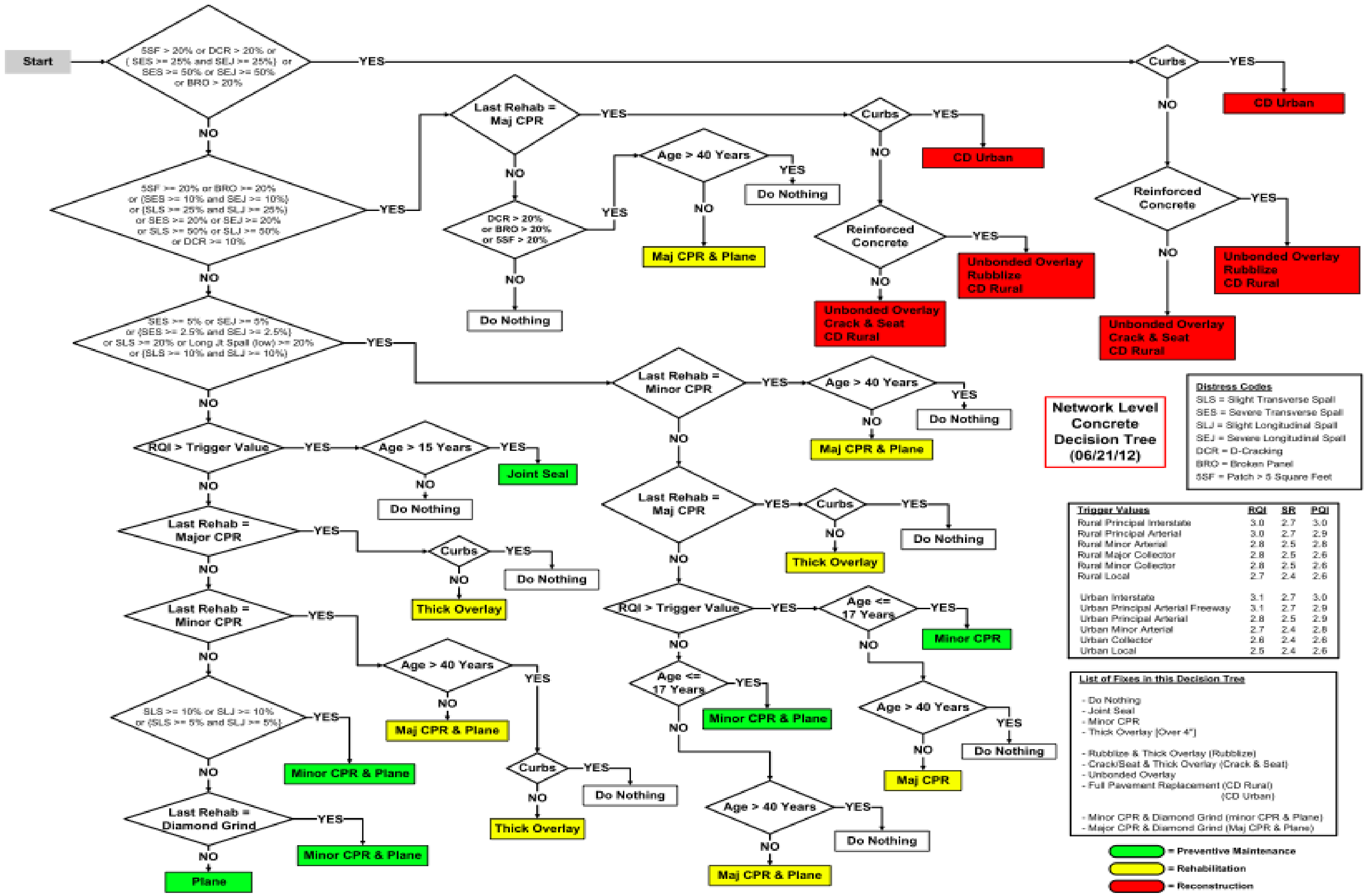


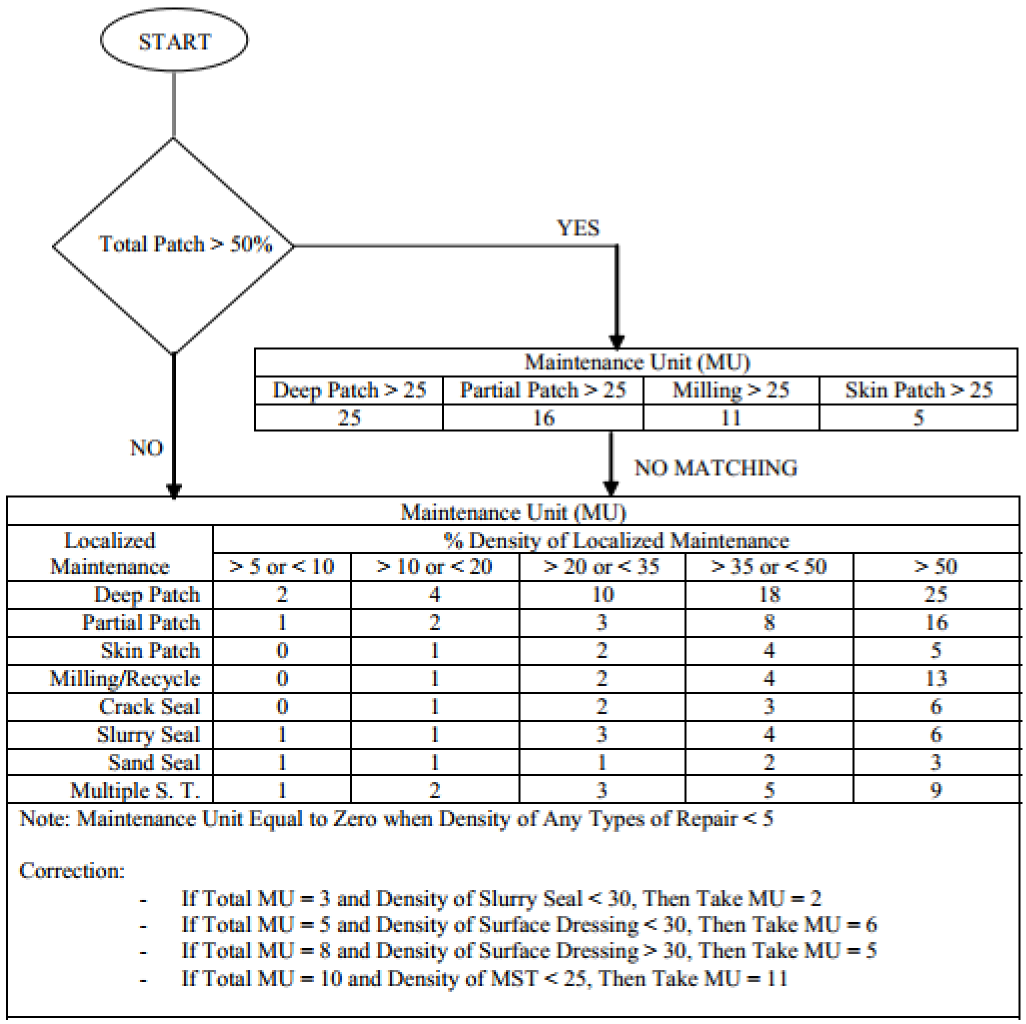
Figure 2.1 Example of Network Level Concrete Decision Tree Minnesota DOT (2012)

Table 2.1 Nebraska Flexible Pavement Maintenance Decision Matrix (Nebraska Pavement Maintenance Manual 2002)

Flexible Pavement Distress	**Low**		**Moderate**		**High**	
	Occasional	**Frequent**	**Occasional**	**Frequent**	**Occasional**	**Frequent**
Alligator Cracking	3,1	3,6	6,3,11,4	6,5	13,6,11	15,13
Edge Cracking	1,2	2,1	2,13	2,13	13	13
Longitudinal Cracking	2,1	2,6,1	2,6	2,6	13,2,6	6,2,13
Random/Block Cracking	2,1	2,3	2,6	2,6	6,11,12	12,6,14
Raveling/Weathering	3,1,6	3,6,5	6,4	6,4	6,11,5	6,12,11
Distortion	1,8,13	13,1,8	8,13,2	8,13,6,2	8,11,6,13	8,14,13
Rutting	1	1	8+6	8+6	8+6,12	8,14,12
Excess Asphalt	1	1,6	6,1,8	6,8	8+6	8+6 or 12
Transverse Cracking	2,1	2	2,6	2,6	2,6	2,6,13

Numbers inside the table represent treatment types: 1-Do Nothing, 2-Crack Seal/Fill, 3-Fog Seal, 4-Scrub (Broom) Seal, 5-Slurry Seal, 6-Chip Seal/Armor Coat, 7-Micro Surfacing, 8-Mill, 9-Cold-in-place Recycle 10-Hot-in-place Recycle, 11-Thin Cold Mix Overlay, 12-Thin Hot Mix Overlay, 13-Patching, 14-Thick Overlay, 15-Total Reconstruction.

Abo-Hasheme et al. (2004) developed a decision support system called Maintenance Unit (MU) for developing countries to identify M&R activities based on visual inspection information. This Maintenance Unit was developed for both local highway and major highway in Egypt, and its decisions were made based on density of localized maintenance. A total maintenance unit value for each section can be known from the MU table, and based on this number the recommended M&R is identified. The developed MU decision table used to obtain the total value of MU for major highway is shown in Figure 2.2, and the corresponding recommended M&R alternatives can be determined by Table 2.2.



Maintenance Unit (MU)			
Deep Patch > 25	Partial Patch > 25	Milling > 25	Skin Patch > 25
25	16	11	5

Maintenance Unit (MU)					
Localized Maintenance	% Density of Localized Maintenance				
	> 5 or < 10	> 10 or < 20	> 20 or < 35	> 35 or < 50	> 50
Deep Patch	2	4	10	18	25
Partial Patch	1	2	3	8	16
Skin Patch	0	1	2	4	5
Milling/Recycle	0	1	2	4	13
Crack Seal	0	1	2	3	6
Slurry Seal	1	1	3	4	6
Sand Seal	1	1	1	2	3
Multiple S. T.	1	2	3	5	9

Note: Maintenance Unit Equal to Zero when Density of Any Types of Repair < 5

Correction:

- If Total MU = 3 and Density of Slurry Seal < 30, Then Take MU = 2
- If Total MU = 5 and Density of Surface Dressing < 30, Then Take MU = 6
- If Total MU = 8 and Density of Surface Dressing > 30, Then Take MU = 5
- If Total MU = 10 and Density of MST < 25, Then Take MU = 11

Figure 2.2 Maintenance Units for Major Highways in Egypt (Abo-Hasheme et al. 2004)

Table 2.2 Recommended Maintenance Vs Maintenance Unit for Major Highways (Abo-Hasheme et al. 2004)

Recommended Maintenance	**Maintenance Unit (MU)**
Reconstruction Up to Subgrade	>20
Reconstruction Up to W.C. & B.B.C.	>15 or =<20
Structure Overlay After Milling	>12 or =<15
Thin Overlay after Milling	>10 or =<12
Multiple Surface Treatment	>8 or =<10
Slurry Seal	>5 or =<8
Thin Overlay Without Milling	>3 or =<5
Sand Seal	>2 or =<3
Surface Preparation Only (Distress by Distress)	=<2

2.3 Stochastic Methods Used in Infrastructure and Pavement M&R Selection

The major objectives of a network-level pavement management system are to develop short-term and long-term budget need estimates and to produce a list of potential projects based on a limited budget. The optimum approach to achieve these objectives relies heavily on the prediction of pavement performance and life-cycle cost analysis of all feasible maintenance and rehabilitation strategies (Butt et al. 1994).

Uncertainty in the outcome of condition measurement has not been addressed in the existing M&R decision models. This uncertainty affects M&R decisions because a measurement error can lead to the selection of a “wrong” M&R activity, which will be translated into an increase in the total lifecycle cost of an infrastructure facility if that activity is implemented. This increase in lifecycle costs becomes more pronounced when measurements are repeated throughout the lifecycle of that facility.

Madanat (1991) presents a Latent Markov Decision Process (LMDP) methodology for M&R activity selection, which accounts for the presence of both forecasting and measurement uncertainty. This LMDP methodology is an extension of the traditional MDP methodology, but it assumes that the measurement of facility condition is not error-free.

Guillaumot (2003) provides an adaptive optimization model, which integrates latent Markovian decision process formulations and adaptive control formulations, to solve the problem of finding joint inspection and maintenance policies for infrastructure facilities. This model accounts for the uncertainties in initial performance model and expected total cost of managing a facility.

Ferreira (2002) developed a new probabilistic segment-linked optimization model for network-level pavement management systems by combining the optimization model used in Arizona and Singapore systems. This model considers the uncertainty inherent to the evolution of pavement condition states, and clearly recognizes the segments of the road network where the M&R treatment should be applied.

Ben-Akiva et al. (1993) presents a framework for the analysis of infrastructure performance and the planning of inspection, maintenance, and rehabilitation activities. This framework identifies the errors inherent in the measurement of condition indicators and facility performance model by using Latent Markov Decision Process.

2.4 Monte Carlo Simulation

Monte Carlo simulation is a class of computational algorithms that rely on repeated random sampling from distributions of probabilistic inputs to obtain numerical results. Although Monte Carlo simulation has not been widely used in pavement management, it has been used in other engineering and non-engineering disciplines.

In the biology and biochemistry, for example, Monte Carlo simulation it has been used widely to model molecular activity and genetics and evolutionary studies. Berney and Danuser (2003) described their use of Monte Carlo simulation when modeling the fluorescence resonance energy transfer technique, which measures the interactions between two molecules. LeBlanc et al (2003) described the use of Monte Carlo simulation of molecular systems belonging to complex energetic landscapes, and offered a new approach to improve the convergence of these simulations. Korol et al (1998) used Monte Carlo simulation to demonstrate the advantages of multi-trait analysis in detection of linked quantitative trait effects. Salamin et al (2005) have used Monte Carlo simulation to reconstruct large trees such as the Tree of Life, with parameters inferred from four large angiosperm DNA matrices, which could radically assist researchers in creating this tree.

In construction management, the application of Monte Carlo simulation is often mentioned under the topic of risk management, although it can also be seen in time management and cost management (Kwak et al. 2007). Williams (2003) contoured the process of Monte Carlo simulation use in project management and helps the project manager to answer the probabilistic questions. Smith (1994) outlined how simulation assists managers in choosing among different potential investments and projects. He explained that by replacing estimates of net cash flow for each year with probability distributions for each factor affecting net cash flow, managers can develop a distribution of possible Net Present Values of an investment instead of a single value. Sadeghi (2010) et al. proposed a Fuzzy Monte Carlo Simulation framework for risk analysis of construction projects. This framework a fuzzy cumulative distribution function was constructed as a novel way to represent both fuzzy and probabilistic uncertainty. Gilchrist et al (2003) have developed a Monte Carlo simulation model that allows construction contractors to predict and mitigate the occurrence and impact of construction noise on their projects. This model was tested and validated using field measurements during various stages of the construction of an eight-story parking garage in London, Ontario, Canada.

In pavement engineering, Walls (1998) recommended procedures for conducting life-cycle cost analysis (LCCA) of pavements and introduced a probabilistic approach to account for the uncertainty associated with LCCA inputs. Monte Carlo simulation was used to incorporate variability associated with LCCA inputs into the final results.

3. DATASET DEVELOPMENT

This research uses data obtained from TxDOT's PMIS database and the 2012-2015 PMP for the Bryan district. The PMP lists planned pavement M&R projects (including project location and treatment type), estimated costs, and construction year. TxDOT's PMIS database contains valuable data like pavement inventory, condition, and traffic for data collection sections (typically 0.5-mile long). Therefore, by matching and merging the PMP projects to their corresponding PMIS sections, a more comprehensive dataset about pre-treatment pavement condition, M&R unit cost, traffic, was developed. The obtaining and organization of data is discussed in the following sections of this thesis.

3.1 Overview of PMIS Data

TxDOT is currently responsible for maintaining approximately 193,000 lane-miles of highways, and has a statewide goal of having 90% of pavement lane-miles in "Good" or better condition by fiscal year 2012. TxDOT uses PMIS to help reach this goal and manage this pavement network effectively. PMIS is an automated system used to store, retrieve, analyze, and report information to help with pavement related decision-making process. TxDOT's PMIS database contains more than 195,000 data collection sections, which make up the entire network of State-maintained highways (TxDOT PMIS Rater's Manual, 2011).

In the fall of each year, all pavements are rated in sections that typically range from 0.1-mile to less than 1.0-mile with visual observations and mechanical measurements (Scullion et al, 1997, Zhang et al, 2009, TxDOT PMIS Rater's Manual, 2011). The pavement scores (i.e., distress score, ride score, and condition score) for each data collection section are calculated based on the pavement evaluation data, and then are stored in the PMIS database. PMIS contains data on hundreds of data items. The following data items listed in Table 3.1 were extracted from PMIS for Bryan district and used in this research:

Table 3.1 Data Information of PMIS

Category	Data Items
Project Location and Identification	Highway System, Highway Number, Roadbed ID, BRMN, ERMN and displacement
Pavement Condition Data	Distress Score, Ride Score and International Roughness Index (IRI)
Traffic Data	ADT
Inventory Data	Number of Lanes, Section Length, and Pavement Type

3.2 Overview of PMP Data

In Texas, each district of TxDOT is required to develop a four-year pavement management plan and update that plan every year. The 4-year PMPs offer TxDOT with a mechanism to predict pavement conditions based on a specified funding level and project-specific plan. The detailed information listed in PMPs is summarized in Table 3.2.

Table 3.2 Data Information of PMP

Category	Data Attributes
Jurisdiction	District Number and County Number
Project Location and Identification	Highway System, Highway Number, Roadbed, Direction, BRMN, ERMN and displacement
M&R Type and Cost	Project Class (M&R Treatment Type), M&R Cost, and Layman's Description
M&R Treatment Time	Year, District Let Date

3.3 Forming New Dataset by Matching PMP Projects to PMIS Sections

To determine the PMIS sections that constitute each PMP project, these sections were matched to the beginning and ending limits of each M&R project listed in the PMP. This process allowed for computing a unit cost and measuring condition variability for each M&R project listed in the PMP.

Each PMIS data collection section is identified by District number, County number, highway ID, reference marker and displacement (see Figure 3.1, for example).

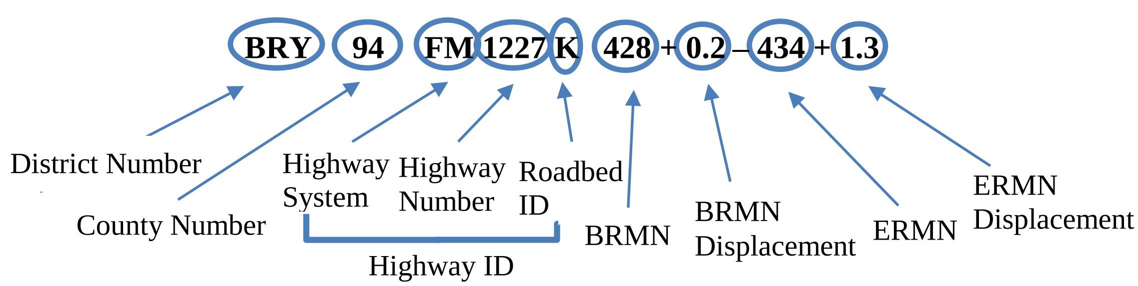


Figure 3.1 Example of Highway Location Information

Highway ID is the composition of highway system, highway number, and the roadbed ID. Highway system is the code designated by the Texas Transportation

Commission to describe the signing of a highway section (see Table 3.3). Roadbed ID (see Figure 3.2) is the code used to identify separate roadbeds that constitute a highway section at which point the measurement begins, and K means single main lanes road, L means left main lanes road, R means right main lanes road, X means left frontage road, A means right frontage road. For example, IH0045X means that the highway system is Interstate Highway, highway number is 0045, and the roadbed ID is X, which represents the left frontage roadbed.

Table 3.3 Highway Systems and their Abbreviations in Texas

Abbreviation	**Route Description**
IH	Interstate Highway
US	US Highway
SH	State Highway, includes NASA, OSR
BI	Business Interstate
BU	Business US Highway
BS	Business State Highway
FM	Farm to Market
BF	Business Farm to Market
PR	Park Road

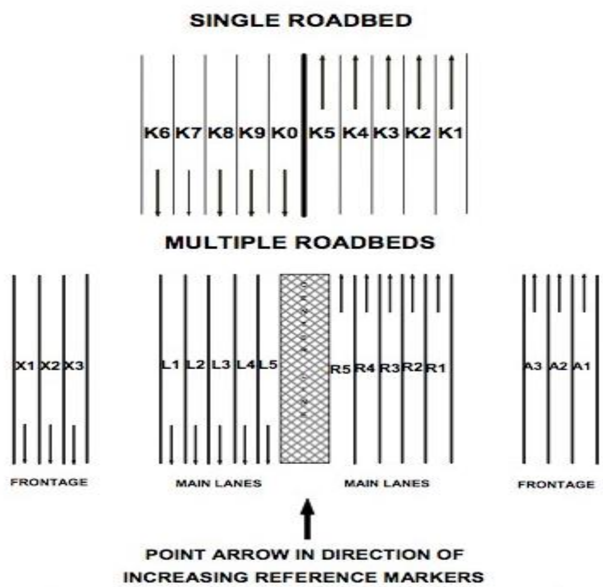


Figure 3.2 Roadbed ID Code

Reference maker is a number placed below the highway route sign at approximately 2-mile intervals, which is used to identify the mile point on a highway. Displacement is used to specify the distance from a reference maker in tenths of a mile. For example, a project beginning reference marker number (BRMN) is “554+0.0” indicates that the project begins 0.0 miles from RMN 554. The ending reference marker number (ERMN) “562+0.3” indicates that the project ends 0.3 miles past RMN 562.

By matching each M&R project to its corresponding PMIS data collection sections, a dataset was formed and used in this research. The new dataset includes data from both PMIS and PMP, as described in Table 3.4. Appendix A lists the M&R projects used in this study.

Table 3.4 Data Items in the Research Dataset and their Sources

Data Item	PMIS	PMP
Year		✓
District Number		✓
County Number		✓
Highway System	✓	✓
Highway Number	✓	✓
Roadbed ID	✓	✓
BRMN	✓	✓
BRMN Displacement	✓	✓
ERMN	✓	✓
ERMN Displacement	✓	✓
M&R Treatment Category (Project Class)		✓
M&R Cost		✓
Layman's Description		✓
Distress Score	✓	
Ride Score	✓	
IRI	✓	
ADT	✓	
Number of Lanes	✓	
Section Length	✓	
Pavement Type	✓	

3.4 Pavement Performance Indicators

In this study, distress score and ride score are used to describe the condition pavement. These indicators are direct inputs to the M&R selection decision tress (see Section 5) and simulation process (See Sections 4 and 6) developed in this research. Distress score and ride score are explained in further details next.

3.4.1 Distress Score

Distress score (DS) is a pavement surface distress index used by TxDOT to rate pavement according to the type and amount of key distresses present. DS has a 1–100 scale (with 100 representing no or minimal distress).

Equation (3-1) and (3-2) are used for computing DS. These equations were developed for Texas in the 1990s (Stampley et al. 1995).

$$U_i = \begin{cases} 1.0 & \text{when } L_i = 0 \\ 1 - \alpha e^{-\left(\frac{\rho}{L_i}\right)^{\beta}} & \text{when } L_i > 0 \end{cases} \quad (3\text{-}1)$$

$$DS = 100 \times \prod_{i=1}^{n} U_i \quad (3\text{-}2)$$

L_i is the density of individual distress types in the pavement section. It is expressed as quantity of distress per mile, quantity of distress per section area, quantity of distress per 100-ft, etc., depending on the distress type. For asphalt pavements, for example, eight distress types are considered—shallow rutting, deep rutting, failures, block cracking, alligator cracking, longitudinal cracking, transverse cracking, and patching. Ride L_i represents the percent of ride quality lost over time. U_i is a utility value (ranging between zero and 1.0) and represents the quality of a pavement in terms of overall usefulness (e.g., a U_i of 1.0 indicates that distress type *i* is not present and thus is most useful). As shown in Figure 3.3, coefficients α (maximum loss factor), β (slope factor), and ρ (prolongation factor) control the shape of the utility curve, including maximum drop, inflection point, and the slope of the curve at that point.

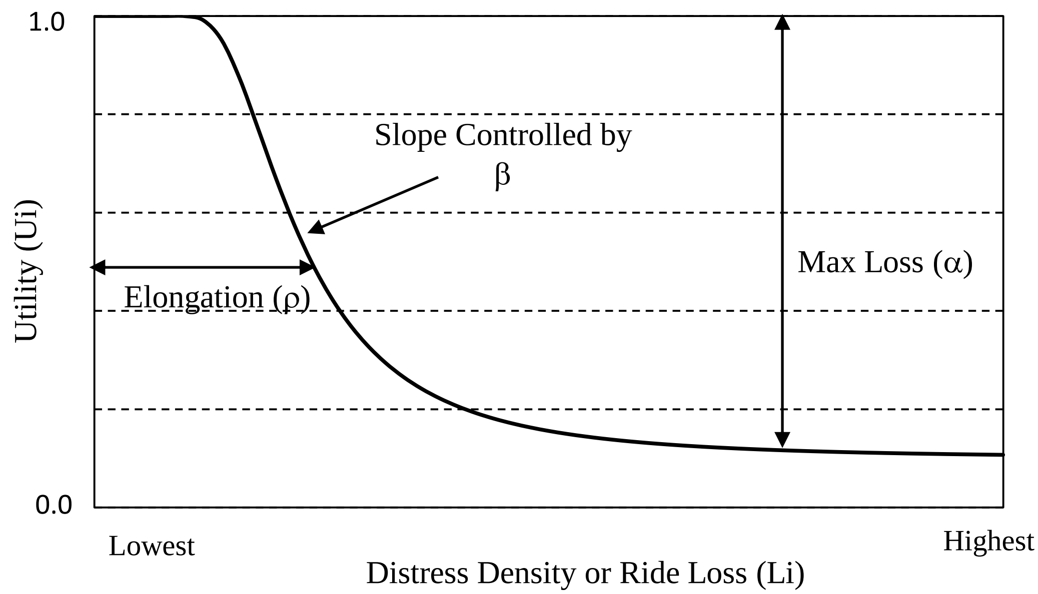


Figure 3.3 General Shape of Utility Curves Used for Computing DS

There are three broad pavement types in PMIS: continuously reinforced concrete pavement (CRCP), jointed concrete pavement (JCP), and asphalt concrete pavement (ACP). Pavement type code stored in PMIS has been used to identify the pavement broad type. The detailed pavement types within each broad type are listed in Table 3.5. The pavement sections used in this study have the detailed types 5, 8 and 10.

Table 3.5 Proposed PMIS Pavement Types

Pavement Type		Description
Broad	**Detailed**	
CRCP	1	Continuously-Reinforced Concrete Pavement
JCP	2	Jointed Concrete Pavement-reinforced
	3	Jointed Concrete Pavement-unreinforced (plain)
ACP	4	Thick Asphalt Concrete Pavement (greater than 14.0 cm thick; [5.5"])
	5	Intermediate Asphalt Concrete Pavement (less than 6.4-14.0 cm thick; [2.5-5.5"])
	6	Thin Asphalt Concrete Pavement (less than 6.4 cm thick; [2.5"])
	7	Composite Pavement (asphalt surfaced concrete pavement)
	8	Overlaid or Widened Old Concrete Pavement
	9	Overlaid or Widened Old Flexible Pavement
	10	Thin-surfaced Flexible Base Pavement (surface treatment or seal coat)

3.4.2 Ride Score

Ride Score (RS) is an index that describes the roughness of a pavement, which ranges from 0.1 (very rough) to 5.0 (very smooth). The 2011 PMIS Technical Manual defines RS as the length-weighted average of all Serviceability Index (SI) values in a data collection section, as follows:

$$RS = \frac{\sum_{i=1}^{n} d_i \times SI_i}{\sum_{i=1}^{n} d_i}$$

where n = number of SI values in the Data Collection Section;

d= length of pavement, in miles, covered by the SI value;

and SI = Serviceability Index (from Profiler).

PMIS computes SI from the International Roughness Index describes (IRI) measurements, as follows:

$$SI = 8.8532704 - 4.425873 \times \left[\frac{0.5 \times (L_{IRI} + R_{IRI})}{63.36} \right]^{0.35}$$

where L_{IRI} = IRI for left wheel path;

and R_{IRI} = IRI for right wheel path.

IRI describes the amount of roughness within a given length of pavement (inches per mile) – higher values mean more roughness.

4. PROBABILITY DISTRIBUTIONS FOR DISTRESS SCORE, RIDE SCORE AND UNIT COST

This section of the thesis describes the development of probability distributions for unit cost and pre-treatment condition of M&R projects. These probability distributions represent uncertainty in key inputs to pavement needs analysis.

4.1 Method of Developing Probability Distributions

Probability distributions can be developed using empirical data or subjective probabilities (e.g., expert opinion). In this research, the @Risk software was used to help fit M&R unit cost, distress score, and ride score empirical data to commonly-used probability distribution types. As discussed earlier, this empirical data was obtained from TxDOT's PMIS and PMP databases.

The @Risk software identifies probability distribution types that best describe the variability in the data. The recommended best fit is determined based on statistical indicators that describe the goodness of fit, such as Chi-squared, Anderson-Darling (A-D), and Kolmogorov-Smirnov (K-S) (Palisade Corporation Guide to using @ Risk 2004).

The following steps were followed to select the best fit probability distribution for M&R unit cost and pre-treatment condition indicators (i.e., distress score, ride score).

- Step 1. Select Data Type

In the step, the data type is selected as either discrete or continuous. Discrete distributions return integer values. For example, a dataset of the outcome of flip-a-coin trials (i.e., can be either head or tail) can only be fit to discrete distributions because partial number of tails is not possible.

In contrast, continuous distributions can return any value in a range, for example, a set of data describing pavement thickness. Unit cost, distress score, and ride score analyzed in this research are all continuous variables.

- Step 2. Decide Domain Limits

  For continuous data sets, the upper and lower limits of the distributions can be specified before fitting the data. In the @Risk software, there are four limit types: fixed bound, bounded but unknown bound, open bound, and unsure. These limit types are described as follows:

  - Fixed Bound:This type allows the user to specify upper limit value and or lower limit value for the probability distribution. For example, as discussed earlier, the value of DS ranges from 0 to 100. Thus, in this case, the upper limit fixed bound was set to 100 and the lower limit fixed bound was set to zero.
  - Bounded But Unknown Bound: This limit type is similar to the fixed bound type; however, unlike a fixed bound, the limit value is determined by @Risk as it performs the best fit. If bounded but unknown bound was used, the distribution type can only be Triangular distribution, BetaGeneral distribution, Pert distribution,

and Uniform distribution. This type was used in some cases where the frequency distribution is concentrated in the middle (e.g., DS ranging from 50 to 80).

- Open Bound: For the open bound, the limit of the distribution must extend to either plus infinity (for an upper limit) or minus infinity (for a lower limit). This type was not applicable to any of the variables considered in this research (i.e., DS, RS, and unit cost).
- Unsure Bound: The unsure bound is the default option in @Risk, which is a combination of the unknown bound and the open bound. The limits of distributions that are non-asymptotic are treated as in the unknown bound case, while asymptotic distributions are still included as in the open bound case. This type was used in this research in some cases, such as preventive maintenance unit cost distribution fits.

- Step 3. Run @Risk and Select the Best-Fit Probability Distribution

Finally, the fitting process is run and the best-fit probability distribution for each variable in question is selected. This selection is made based on visual assessments and statistical indicators.

@Risk generates various types of graph to help visually assess the quality of fitted probability distributions: comparison graphs, P-P graphs, and Q-Q graphs. These graphs are described as follows:

- Comparison Graph: A comparison graph superimposes the input data and fitted distribution on the same graph to visually compare them. For example, Figure 4.1 shows an example comparison graph for preventive maintenance project No. 16 distress score distribution.

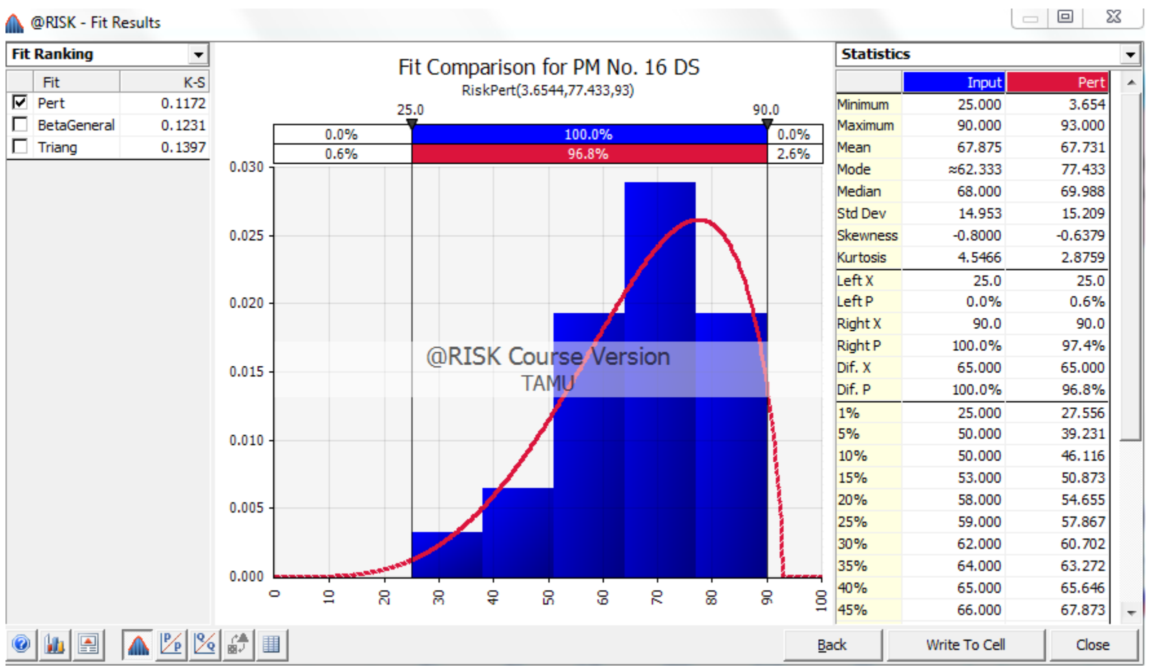


Figure 4.1 Example Comparison Graph for Project No. 14 DS Distribution

- P-P Graph: Probability-Probability (P-P) graph plots the distribution of the input data (P_i) vs. the distribution of the result ($F(x_i)$). If the fit is "good", the plot will be nearly linear. It is only available for sample data fits. For example, Figure 4.2 shows an example P-P graph for preventive maintenance project No. 8 distress score distribution.

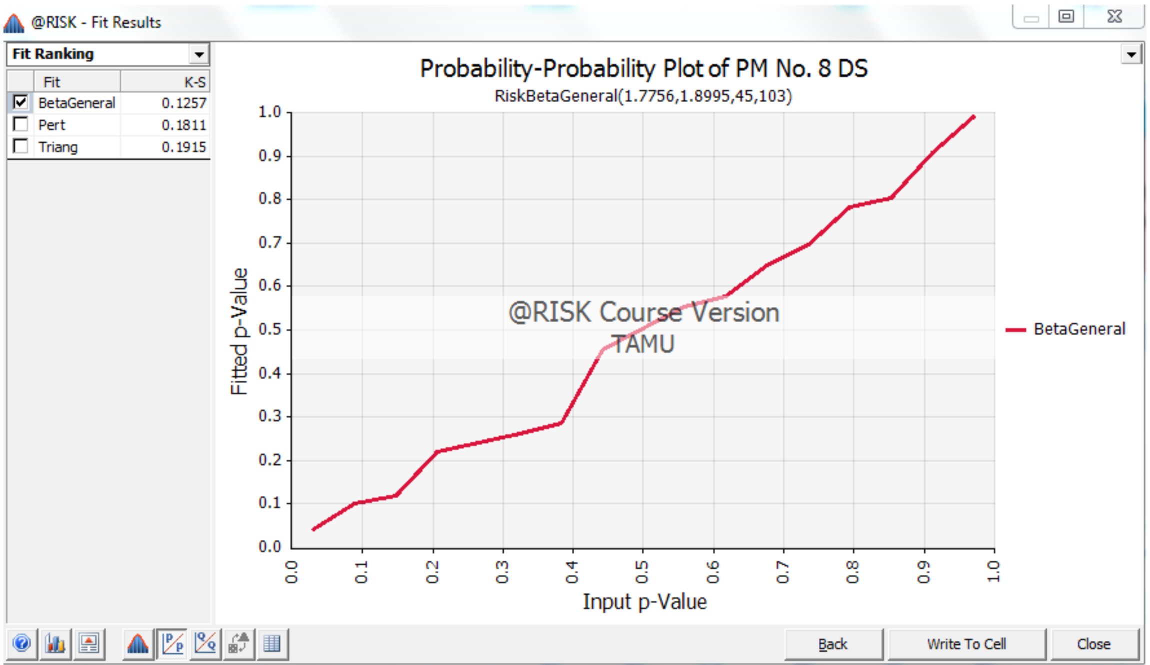


Figure 4.2 Example P-P Graph for PM Project No. 8 DS Distribution

- Q-Q Graph: Quantile-Quantlie (Q-Q) graph plots percentile values of the input distribution (x_i) vs. percentile values of the fitted distribution $(F^{-1}(P_i))$. If the fit is “good”, the plot will be nearly linear. It is only available for continuous sample data fits. For example, Figure 4.3 shows an example Q-Q graph for preventive maintenance project No. 5 ride score distribution.

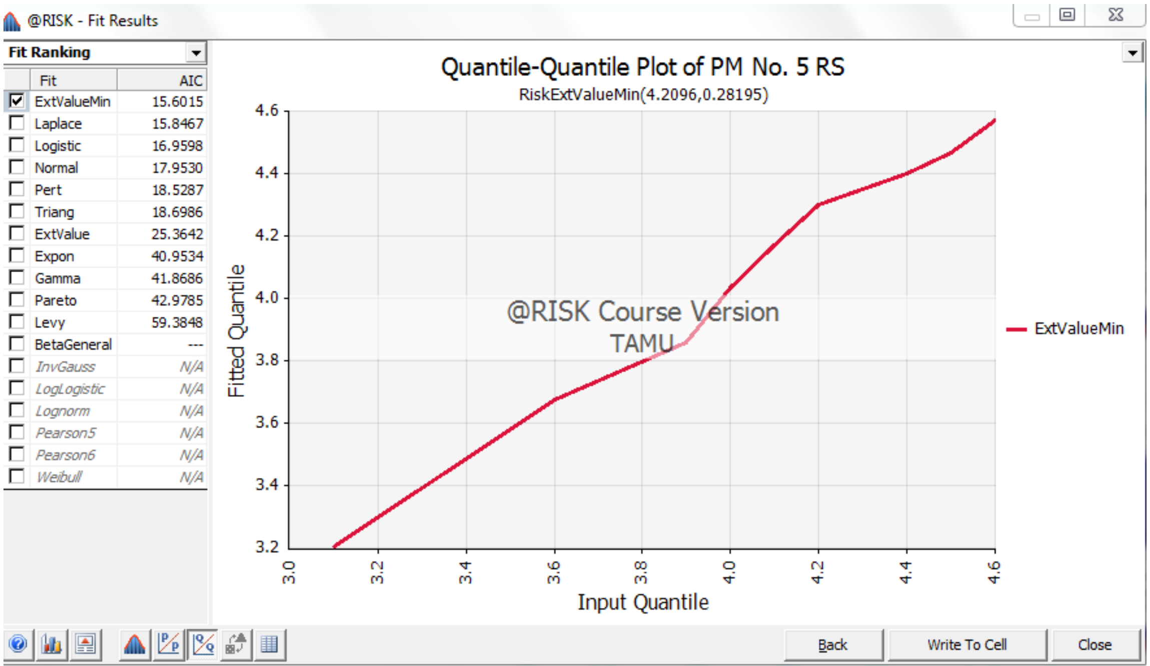


Figure 4.3 Example Q-Q Graph for PM Project No. 4 RS Distribution

In addition to the above graphs, @Risk provides five fit statistics to help choose the best fitted probability distribution. These statistics measure how good the distribution fits the input data and how confident the analyst is that the data was produced by the fitted distribution function. For each of these statistics, the smaller the value, the better the fit. These five statistics are listed in following:

- Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC): The AIC and BIC model selection criteria statistics are calculated from the log-likelihood function and take into account the number of free parameters of the fitted distribution. As opposed to constants and other parameters that are restricted to represent meaningful data, free parameters can be adjusted to make the models fit the data. In other words, the smaller the number of free parameters, and the better the fitted distribution is.

- Chi-square Statistic: The chi-square statistic is a commonly used goodness-of-fit statistic, which can be used with both continuous and discrete sample data. The x-axis domain must be divided into several "bins" and then it is defined as:

$$\chi^2 = \sum_{i=1}^{K} \frac{(N_i - E_i)^2}{E_i}$$

Where

K: the number of bins

N_i: the observed number of samples in the i^{th} bin

E_i: the expected number of samples in the i^{th} bin.

A weakness of the chi-square statistic is that different conclusions from the same data can be reached if different bins were specified. @Risk can eliminate some of this arbitrariness by trying to make each bin contain an equal amount of probability.

- Kolmogorov-Smirnov Statistic: The Kolmogorov-Smirnov (K-S) statistic is defined as following:

$$D_n = \sup\left[\left|F_n(x) - \hat{F}(x)\right|\right]$$

Where

n: total number of data points

$\hat{F}(x)$: the fitted cumulative distribution function

$F_n(x) = \frac{N_x}{n}$

N_x: the number of X_i less than x

The K-S statistic is less arbitrary than the chi-squared statistic because it does not require binning. However, a weakness of it is that the tail discrepancies cannot be detected very well.

- Anderson-Darling Statistic: The Anderson-Darling (A-D) statistic that can be defined as following:

$$A_n^2 = n\int_{-\infty}^{+\infty} \left[F_n(x) - F_o(x)\right]^2 \psi(x) f_o(x) dx$$

Where

n: total number of data points

$\psi(x) = \frac{1}{F_0(\mathrm{x})\left[1 - F_0(\mathrm{x})\right]}$

$f_0(\mathrm{x})$: the hypothesized density function

$F_0(\mathrm{x})$: the hypothesized cumulative distribution function

$F_n(x) = \frac{N_x}{n}$

N_x: the number of X_i less than x

Like the K-S statistic, the A-D statistic does not require binning. It focuses on the differences between the tails of fitted distribution and input data.

P-value can also be used to describe the likelihood that a sample drawn from the fitted distribution would generate a fit statistic greater than or equal to the fit statistic that was obtained from the original dataset. This probability is sometimes referred as “observed significance level” of the test. As the P-value decreases to zero, there is less confidence that the fitted distribution could possibly have generated the original dataset. Conversely, as the P-value approaches one, it is unlikely to reject the hypothesis that the fitted distribution actually generated the original dataset.

4.2 Unit Cost Probability Distribution

As mentioned earlier, pavement M&R treatment types used by TxDOT include PM, LR, MR, and HR. However, the dataset for this study included a limited number of rehab projects (i.e., seven LR projects and seven MR projects). Thus, the rehab projects were grouped in one category (called Rehab projects). The study dataset contained 237 PM projects. The PM projects were used to fit the PM unit cost distribution and 14 LR and MR projects are used to fit the Rehab unit cost distribution.

The unit cost for each M&R project was calculated using the following equation and then the results were used to fit the probability distributions.

$$Unit\,Cost = \frac{Total\,Cost}{(Number\ of\ \ Lanes)\times\left(\mathrm{Pr}\,oject\ Length\right)}$$

Where, Total Cost is the estimated cost for each M&R project as shown the Bryan district PMP.

The descriptive statistics of PM, LR, and MR unit costs are summarized in Table 4.1. It can be seen that the average and median values of LR and MR are very close, suggesting that the unit costs for LR and MR are similar. Therefore, the LR and MR can be combined together into one category (Rehab).

Table 4.1 Descriptive Statistics for Unit Cost of PM, LR, and MR Projects

M&R Treatment Type	**PM**	**LR**	**MR**
Average	$33,479	$186,532	$203,020
StdDev	$56,999	$102,210	$174,404
Median	$18,727	$173,864	$153,186
Number of Projects	237	7	7

The best fit unit cost probability distributions for PM and Rehab were selected using the process discussed earlier and are shown in Figures 4.4 and 4.5, respectively.

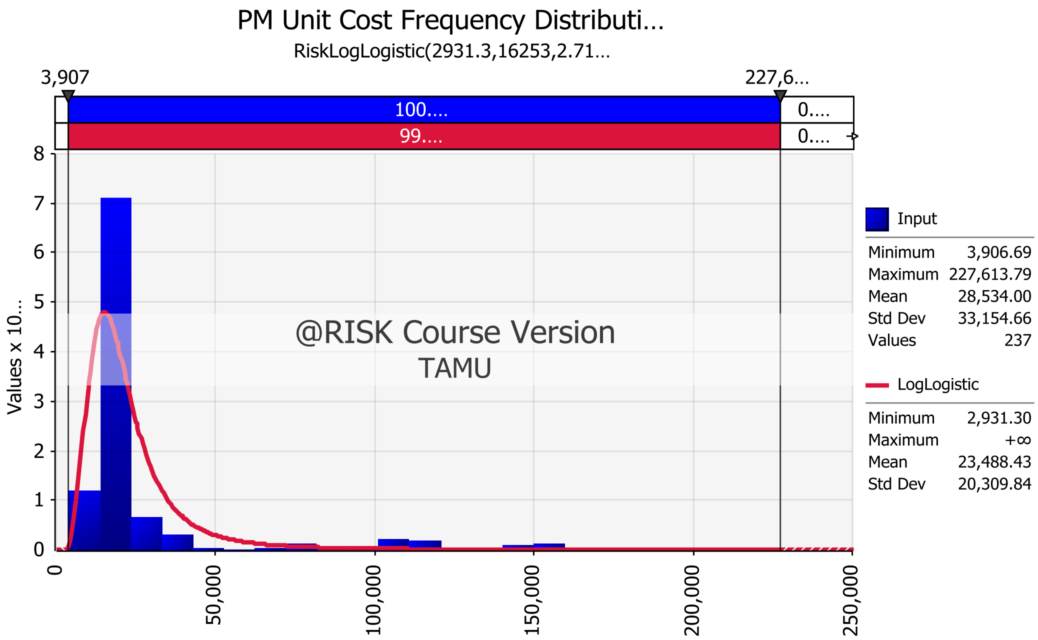


Figure 4.4 PM Unit Cost Probability Distribution

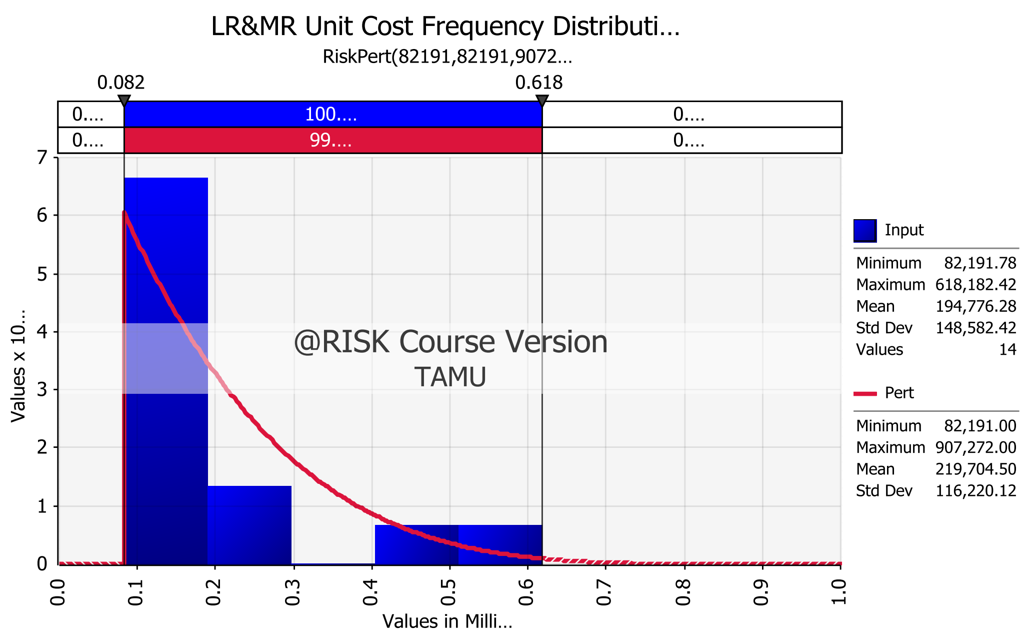


Figure 4.5 Rehab (LR&MR) Unit Cost Probability Distribution

4.3 DS and RS Probability Distributions

@Risk requires that the number of sample data should be greater than five, which means that the number of data collection sections within each project should be greater than five. Only 25 M&R projects (two Rehab projects and 23 PM projects) from 2012 met this criterion and were used to fit probability distributions for distress score and ride score. Two projects are used here as examples to illustrate this data. Table 4.2 shows the pre-treatment DS and RS values for each PMIS section within a 9-mile PM project on highway US79. The fitted DS and RS probability distributions for this project are shown in Figures 4.6 and 4.7, respectively. Similarly, Table 4.3 shows the pre-treatment DS and RS values for each PMIS section within a 6.5-mile PM project on Interstate Highway 45 (IH-45). The fitted DS and RS probability distributions for this project are shown in Figures 4.8 and 4.9, respectively.

Table 4.2 Variability in Pre-treatment DS and RS within 9-mile PM project form 2012 on US79

Fiscal Year	Highway Number	BRMN	BRMN Displ	ERMN	ERMN Displ	Distress Score	Ride Score
2012	US0079 K	0480	1.5	0482	0	89	4.2
2012	US0079 K	0482	0	0482	0.5	81	4.4
2012	US0079 K	0482	0.5	0482	1	95	4.1
2012	US0079 K	0482	1	0482	1.5	97	4.2
2012	US0079 K	0482	1.5	0484	0	94	4.1
2012	US0079 K	0484	0	0484	0.5	98	4
2012	US0079 K	0484	0.5	0484	1	95	4
2012	US0079 K	0484	1	0484	1.5	90	4.2
2012	US0079 K	0484	1.5	0486	0	92	4.4
2012	US0079 K	0486	0	0486	0.5	94	4.4
2012	US0079 K	0486	0.5	0486	1	92	4.4
2012	US0079 K	0486	1	0486	1.5	78	4.2
2012	US0079 K	0486	1.5	0488	0	85	4.1
2012	US0079 K	0488	0	0488	0.5	80	4
2012	US0079 K	0488	0.5	0488	1	83	4.3
2012	US0079 K	0488	1	0488	1.5	93	4
2012	US0079 K	0488	1.5	0488	1.8	90	3.6
2012	US0079 L	0488	1.8	0490	0	100	3.5
2012	US0079 L	0490	0	0490	0.6	58	3.5
2012	US0079 R	0488	1.8	0490	0	99	4
2012	US0079 R	0490	0	0490	0.6	83	3.7

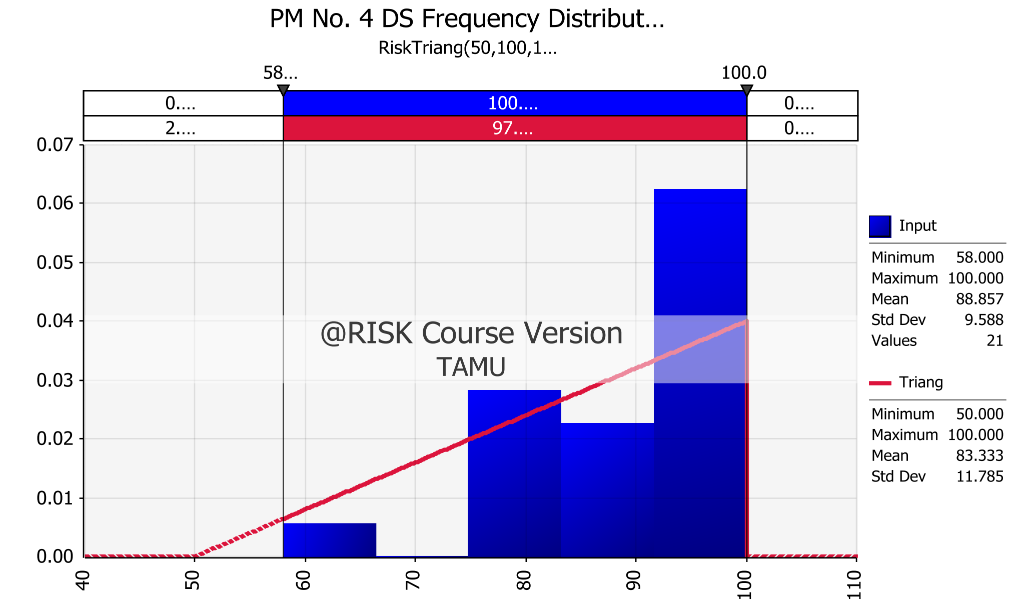


Figure 4.6 DS Probability Distribution Fitted for a 9-mile PM Project on US79 form 2012

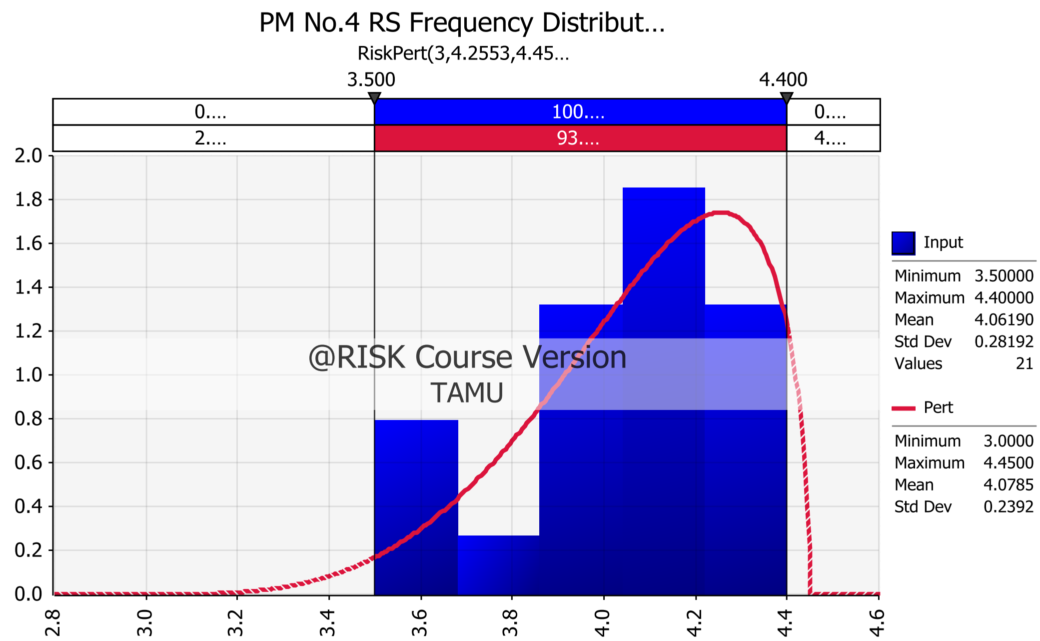


Figure 4.7 RS Probability Distribution Fitted for a 9-mile PM Project on US79 form 2012

Table 4.3 Variability in Pre-treatment DS and RS within 6.5-mile PM project form 2012 on IH-45

Fiscal Year	Highway Number	BRMN	BRMN Displ	ERMN	ERMN Displ	Distress Score	Ride Score
2012	IH0045 L	198	0	198	0.5	72	4.1
2012	IH0045 L	198	0.5	199	0	72	4.1
2012	IH0045 L	199	0	199	0.5	68	4
2012	IH0045 L	199	0.5	200	0	68	4.4
2012	IH0045 L	200	0	200	0.5	71	4.2
2012	IH0045 L	200	0.5	201	0	74	3.7
2012	IH0045 L	201	0	201	0.5	71	4.3
2012	IH0045 L	201	0.5	201	0.8	65	4.1
2012	IH0045 L	201	0.8	202	0	67	4.4
2012	IH0045 L	202	0	202	0.5	67	4.2
2012	IH0045 L	202	0.5	202	0.8	68	4.5
2012	IH0045 L	202	0.8	203	0	70	3.5
2012	IH0045 L	203	0	203	0.5	70	4.3
2012	IH0045 L	203	0.5	204	0	65	4.2
2012	IH0045 L	204	0	204	0.5	84	4.5

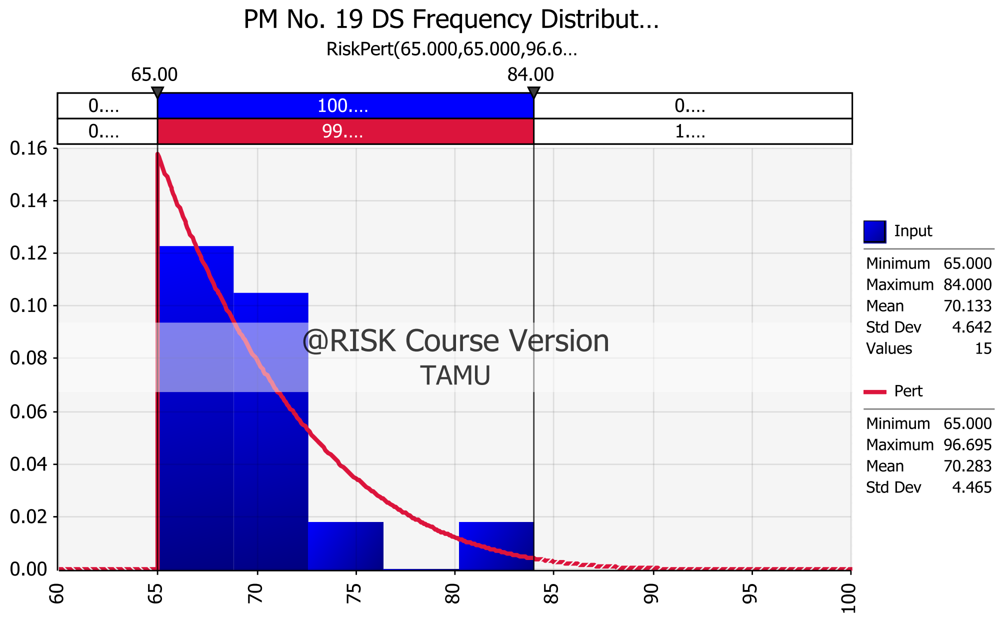


Figure 4.8 DS Probability Distribution Fitted for a 6.5-mile PM Project on IH-45 form 2012

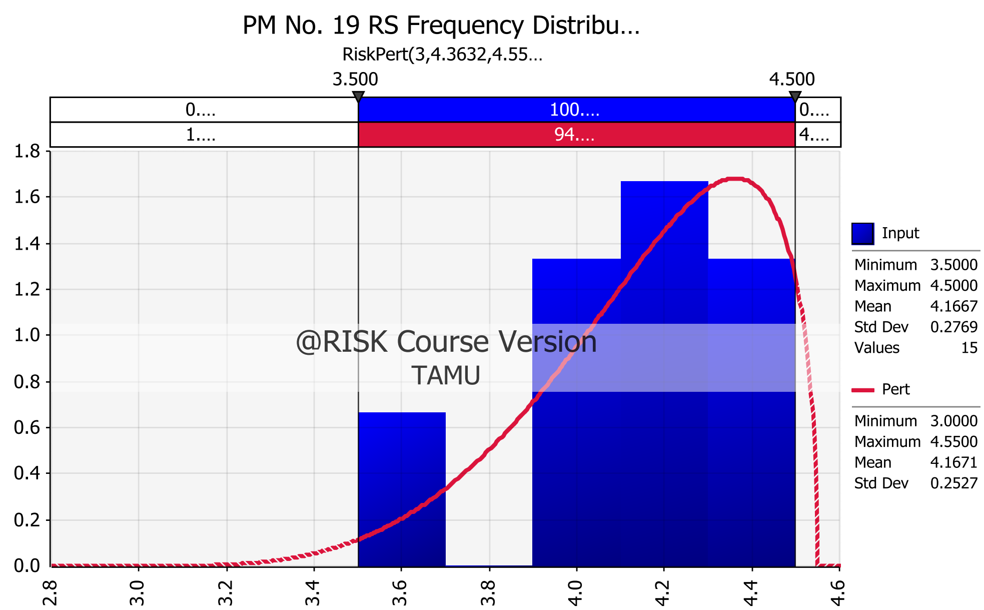


Figure 4.9 RS Probability Distribution Fitted for a 6.5-mile PM Project on IH-45 form 2012

4.4 Summary of Fitted Probability Distribution

Table 4.4 shows the sample size and the probability distributions fitted in this study for each variable (i.e., PM unit cost, Rehab unit cost, pre-treatment DS, and pre-treatment RS) of each M&R project.

Table 4.4 Probability Distributions Fitted in This Study

No.	Variable	Sample Size	Distribution
1	PM Unit Cost	237	LogLogistic(2931.3,16253,2.7102)
2	Rehab Unit Cost	14	Pert(82191,82191,907272)
3	PM Project 1 DS	6	Pert(55,84.544,99)
4	PM Project 2 DS	9	Pert(40,84.767,103)
5	PM Project 3 DS	7	Triang(51.645,100,100)
6	PM Project 4 DS	21	Triang(50,100,100)
7	PM Project 5 DS	18	BetaGeneral(1.6039,2.5276,40,108.775)
8	PM Project 6 DS	6	Triang(86.566,100,100)
9	PM Project 7 DS	12	Pert(30,76.543,102)
10	PM Project 8 DS	17	BetaGeneral(1.7756,1.8995,45,103)
11	PM Project 9 DS	20	Triang(51.332,100,100)
12	PM Project 10 DS	15	Pert(73.082,100,100)
13	PM Project 11 DS	14	Triang(50,100,100)
14	PM Project 12 DS	19	Triang(57.219,100,100)
15	PM Project 13 DS	6	Triang(75.752,100,100)
16	PM Project 14 DS	25	Triang(50,100,100)
17	PM Project 15 DS	32	BetaGeneral(1.5298,1.0862,37,102)
18	PM Project 16 DS	24	Pert(3.6544,77.433,93)
19	PM Project 17 DS	13	Triang(37.621,100,100)
20	PM Project 18 DS	17	Pert(55.456,65.875,69.54)
21	PM Project 19 DS	15	Pert(65,65,96.695)
22	PM Project 20 DS	18	BetaGeneral(1.2739,1.1873,43,102)
23	PM Project 21 DS	27	Triang(68.691,100,100)
24	PM Project 22 DS	10	Triang(52.777,100,100)

Table 4.4 Continued

No.	Variable	Sample Size	Distribution
25	PM Project 23 DS	12	Triang(79.265,100,100)
26	Rehab Project 1 DS	5	Pert(62,74.403,88)
27	Rehab Project 2 DS	5	Triang(18.232,100,100)
28	PM Project 1 RS	6	BetaGeneral(1.7388,1.0569,2.2,3.6)
29	PM Project 2 RS	9	Pert(3.2,4.5142,4.9)
30	PM Project 3 RS	7	Pert(2,3.4585,3.9)
31	PM Project 4 RS	21	Pert(3,4.2553,4.45)
32	PM Project 5 RS	18	Pert(2.502,4.2874,4.6383)
33	PM Project 6 RS	6	BetaGeneral(2.2425,2.7059,3.7,4.3)
34	PM Project 7 RS	12	BetaGeneral(3.1209,1.4156,3.6,4.35)
35	PM Project 8 RS	17	Pert(3,4.3412,4.45)
36	PM Project 9 RS	20	Pert(3.5,4.1455,4.9)
37	PM Project 10 RS	15	Pert(2.3398,4.3812,4.8582)
38	PM Project 11 RS	14	Triang(3.7,4.8,4.95)
39	PM Project 12 RS	19	Triang(3.7,4.8,4.8)
40	PM Project 13 RS	6	BetaGeneral(1.6317,1.2787,3.3,4)
41	PM Project 14 RS	25	Pert(2,2.902,3.5)
42	PM Project 15 RS	32	Pert(1.6403,2.4926,3.6654)
43	PM Project 16 RS	24	BetaGeneral(1.719,1.3211,1.3,2.9)
44	PM Project 17 RS	13	Lognorm(0.94989,0.63501,Shift(1.85792))
45	PM Project 18 RS	17	Pert(3.4967,4.229,4.55)
46	PM Project 19 RS	15	Pert(3,4.3632,4.55)
47	PM Project 20 RS	18	Pert(1.3184,3.1271,3.3278)
48	PM Project 21 RS	27	BetaGeneral(1.806,1.1731,1.6,4.1)
49	PM Project 22 RS	10	BetaGeneral(1.7898,1.315,2.3,3.8)
50	PM Project 23 RS	12	Lognorm(0.69448,0.46243,Shift(2.33942))
51	Rehab Project 1 RS	5	Triang(2.3,3.5,3.5)
52	Rehab Project 2 RS	5	Triang(2.6,2.6,4.4)

5. DEVELOPING A SIMPLIFIED DECISION TREE

The impact of uncertainty in unit cost and pre-treatment condition on pavement management decisions at network-level (e.g., needs estimate) is investigated through Monte Carlo simulation. To conduct the Monte Carlo simulation, a simplified decision tree was established to simulate the M&R treatment selection process. Decision tree is a decision support tool that incorporates a set of criteria for identifying an appropriate maintenance and rehabilitation treatment.

5.1 Factors Influencing M&R Treatment Selection

Estimating the funding needed to maintain pavement condition at desired levels is an important task for pavement managers. In Texas, PMIS uses an "if-then" decision tree to select the appropriate M&R treatments, which include Needs Nothing (NN), PM, LR, MR, and HR. While there are no exact definitions for these treatment categories, the following definitions are commonly used (Gharaibeh et al. 2012):

- Routine Maintenance (RM): Crack sealing, edge maintenance, patching (pothole repair), level-up, strip/spot seals, milling, joint repair, localized base repairs, localized concrete repairs.
- Preventive Maintenance (PM): Preventive maintenance is applied to sections with minor distresses like transverse and longitudinal cracking and sections show small amounts of shallow rutting and patches. PM treatments include seal coats (chip seals), thin overlays (less than 2 inches), and micro-surfacing treatments for

hot-mix asphalt (HMA) pavement and diamond grinding for portland cement concrete (PCC) pavement.

- Light Rehabilitation (LR): LR treatments include HMA overlay with thickness between 2 and less than 3 inches; pavement widening and application of full width seal coat, base repair and seal; milling, sealing and thin overlay.
- Medium Rehabilitation (MR): Medium rehabilitation is applied to sections demonstrating patching, deep rutting, and a significant amount of shallow rutting. MR treatments include mill and inlay; mill, stabilize base and seal; level up and overlay; widen pavement, level up and overlay or seal coat; 3- to 5-inch HMA overlay; thick overlay (without any other activity such as milling); mill, patch, under seal and inlay; base repair, spot seal, edge repair and overlay; mill, cement stabilize base, and overlay or seal.
- Heavy Rehabilitation (HR): Heavy rehabilitation is applied to pavement sections with major distresses like deep rutting, patches, alligator cracking, and repairs for punchouts. Both the base and surface layers are repaired. HR treatments include reconstruction of the base and surface, milling and thick overlay or similar activities that restore the pavement functional and structural condition to nearly original conditions.

The PMIS decision tree is based on the factors listed below. A sample of PMIS decision tree is shown in Table 5.1

- Pavement type
- Individual distress ratings
- Ride quality
- ADT levels
- Functional class

Table 5.1 Part of PMIS Decision Tree used for M&R Treatment Recommendations

PMIS Needs Estimate Reason Code	**Pavement Treatment Code**	**Needs Estimate Trigger Criterion**
A005	Heavy Rehab	ADT per lane greater than 5000 and Ride Score less than 2.5
A010	Heavy Rehab	ADT per lane greater than 750 and Ride Score less than 2.0
A100	Medium Rehab	ADT per lane greater than 5000 and Ride Score less than 3.0
A105	Medium Rehab	ADT per lane greater than 750 and Ride Score less than 2.5
A200	Light Rehab	Ride Score less than 2.5
A300	Light Rehab	ADT per lane to "High" based on Functional Class and Shallow Rutting greater than 25 percent
A400	Preventive Maintenance	ADT per lane to "Low" based on Functional Class and Shallow Rutting greater than 50 percent
A405	Preventive Maintenance	ADT per lane to "Low" based on Functional Class and Deep Rutting greater than 10 percent

5.2 Determination of M&R Trigger Values

The objective in developing the simplified decision tree was to make the M&R treatment types determined by new decision tree match those listed in PMP. As previously mentioned, the LR and MR categories were combined as a Rehab treatment category because there is no available HR projects in the 2012 PMP and the number of LR and MR projects are small. Furthermore, only the ACP decision tree needed to be established in this study because all considered projects are of this pavement type.

The simplified decision tree considers ADT per lane (ADT/L), RS, and DS. RS and DS are treated in a probabilistic manner (i.e., represented by probability distributions), but ADT/L is treated in a deterministic manner. Thus, the weighted average ADT/L (weighted by PMIS section length) was used as the representative ADT/L value for each M&R project. The weighted ADT/L calculation process is illustrated in the example shown in Table 5.2.

Table 5.2 Example Weighted Average ADT/L (PM Project No.18)

County No.	Highway ID	BRMN	BRMN Disp	ERMN	ERMN Disp	Section Length	No. of Lanes	ADT	ADT/L
82	IH0045R	198	0	198	0.5	0.5	2	13535	6767.5
82	IH0045R	198	0.5	199	0	0.5	2	14705	7352.5
82	IH0045R	199	0	199	0.5	0.5	2	14705	7352.5
82	IH0045R	199	0.5	200	0	0.5	2	14705	7352.5
82	IH0045R	200	0	200	0.5	0.5	2	14705	7352.5
82	IH0045R	200	0.5	201	0	0.5	2	14705	7352.5
82	IH0045R	201	0	201	0.5	0.5	2	14705	7352.5
82	IH0045R	201	0.5	201	0.8	0.3	2	14705	7352.5
82	IH0045R	201	0.8	202	0	0.1	2	14705	7352.5
82	IH0045R	202	0	202	0.5	0.5	2	14705	7352.5
82	IH0045R	202	0.5	202	0.8	0.3	2	14705	7352.5
82	IH0045R	202	0.8	203	0	0.3	2	14705	7352.5
82	IH0045R	203	0	203	0.5	0.5	2	14705	7352.5
82	IH0045R	203	0.5	204	0	0.5	2	14705	7352.5
82	IH0045R	204	0	204	0.5	0.5	2	14705	7352.5
82	IH0045R	204	0.5	205	0	0.5	2	14705	7352.5
82	IH0045R	205	0	205	0.5	0.5	2	14705	7352.5
					Weighted Average ADT/L				**7313.5**

Ideally, the combination of ADT/L, DS trigger value, and RS trigger value that maximizes the match in M&R treatment type between the simplified decision tree and the actual PMP should be used as the trigger value in the decision tress. However, to guide the search for such ideal values, two new parameters were computed as follows:

$$\%\,\mathrm{Re}hab = \frac{Number\ of\ \mathrm{Re}hab\,\mathrm{Pr}ojects\ with\ High\ ADT/L}{\mathrm{Total}\ \mathrm{Re}hab\,\mathrm{Pr}ojects\ Number}$$

$$\%\,PM = \frac{Number\ of\ PM\ \mathrm{Pr}ojects\ with\ High\ ADT/L}{\mathrm{Total}\ PM\ \mathrm{Pr}ojects\ Number}$$

The optimum trigger values would maximize %Rehab and at the same time minimize %PM. After several trial and error iterations, the decision tree and trigger values shown in Figure 5.1 were selected. This simplified decision tree is only applicable to dataset used in this research and is not intended to select the optimal treatment types.

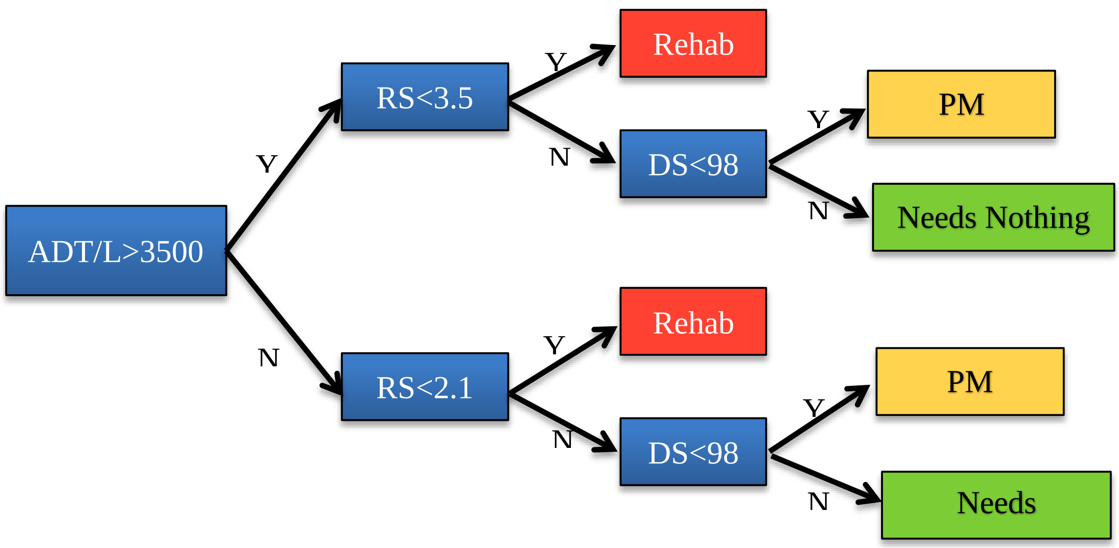


Figure 5.1 Developed Simplified Decision Tree

5.3 Validation of the Simplified Decision Tree

A comparison of M&R treatment recommendations determined by simplified decision tree and listed in Bryan District PMP for 29 M&R projects in 2012 is summarized in Table 5.6. It can be seen that 25 out of the 29 projects have the same M&R treatment type, which demonstrates an 86.2 percent agreement between the simplified decision tress and the district's PMP. The agreement between these two methods in terms of M&R type and project location is displayed visually in the color-coded maps presented in Figures 5.2 and 5.3.

Table 5.3 Comparisons of M&R Recommendations by Using Different Method

Project No.	Highway ID	BRMN	BRMN Displ	ERMN	ERMN Displ	M&R Listed in PMP	M&R determined by decision tree
1	SH0006 A,X	674	1.811	676	1.101	PM	PM
2	SH0036 K	552	0.432	556	0.507	PM	PM
3	SH0036 K,L,R	556	0.507	558	0.637	PM	PM
4	US0079 K,L,R	480	1.522	490	0.403	PM	PM
5	US0079 K	462	1.706	470	1.868	PM	PM
6	US0079 K	478	1.171	480	1.5222	PM	PM
7	US0079 K	458	0.002	462	1.705	PM	PM
8	US0079 K	438	1.662	446	1.69	PM	PM
9	US0079 K	422	1.623	438	0.446	PM	PM
10	US0077 K,L,R	426	2.061	432	1.444	PM	PM
11	US0077 K	432	1.444	438	1.896	PM	PM
12	US0077 K	438	1.896	448	0.958	PM	PM
13	US0190 K	752	1.017	754	1.775	PM	PM
14	FM0050 K	438	0.921	452	0.002	PM	PM
15	SHOSR K	632	0.835	648	1.489	PM	PM
16	SHOSR K	654	1.492	666	1.271	PM	PM
17	FM0039 K	404	1.797	412	0	PM	PM
18	IH0045 R	198	0.047	205	0.473	PM	PM
19	IH0045 L	198	0.047	204	0.448	PM	PM
20	FM1696 K	642	-0.03	650	1.139	PM	PM
21	FM2095 K	582	0.703	594	1.921	PM	PM
22	FM2693 K	672	-0.65	676	0	PM	PM
23	FM2818 K	406	-0.04	410	0.615	PM	PM
24	FM0391 K	396	-0.98	398	0.078	PM	NN
25	FM0488 K	322	0.995	320	-1.91	PM	NN
26	FM1940 K	618	1.067	628	0.05	PM	NN
27	PR0040K	412	-1.92	412	-0.51	PM	NN
28	SH0021 K	620	0	622	0	MR	Rehab
29	FM1179 K	412	0.461	414	0.029	MR	Rehab

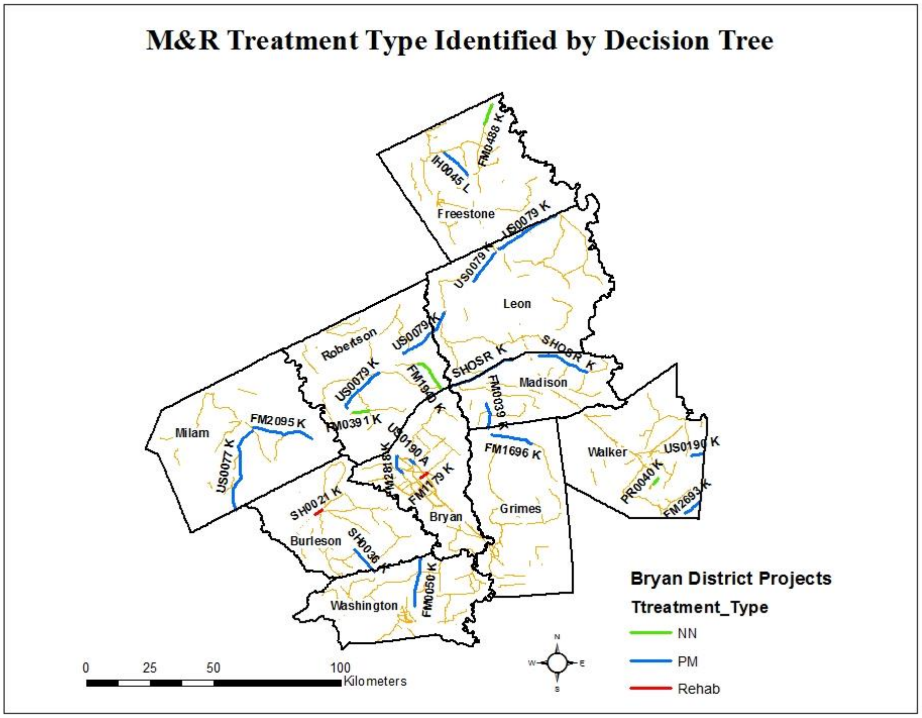


Figure 5.2 Map Displays M&R Projects Identified by the Decision Tree for 2012

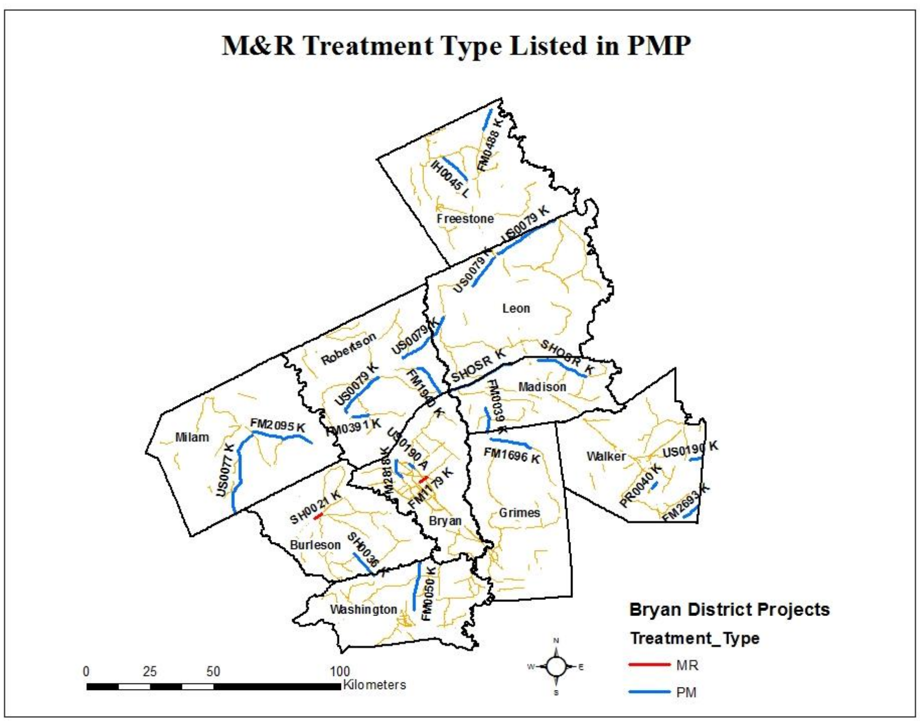


Figure 5.3 Map Displays M&R Projects Listed in the Bryan Distract PMP for 2012

Four of the 29 projects were identified in the district's PMP as PM; while the decision tree identified them as NN. These four projects were further examined as shown in Table 5.4.

Table 5.4 Detailed Information on the Four Inconsistent Projects (Identified in the District's PMP, but not Selected by the Decision Tree)

Highway ID	**Weighted Average DS**	**DS Standard Deviation**	**Weighted Average RS**	**RS Standard Deviation**	**Weighted Average ADT/L**	**Layman Description**
FM0391 K	100	0	3.2	0.3	508	Seal Coat consisting of one surface treatment
FM0488 K	100	0	3.3	0.4	770	Seal Coat consisting of one surface treatment
FM1940 K	100	0	3.4	0.2	513	Seal Coat consisting of one surface treatment
PR0040 K	100	0	2.8	0.2	362	Seal Coat consisting of one surface treatment

This table shows that the weighted average distress score of these four projects are all 100, and the standard deviations are zero, which means that the distress score for all data collection sections is 100. Their ride quality (as measured by RS) is fair to good. Besides, the ADT/L for these four projects is less than 1000 vehicle per day per lane, indicating that these sections have low traffic volume. However, the decision tree does not consider the pavement skid resistance. Thus, perhaps the district's decision to apply Seal Coat was driven by improving skid resistance. Additionally, the application of Seal Coat may have been an attempt to slow deterioration.

6. SIMULATING THE IMPACT OF UNCERTAINTY IN M&R COST AND PRE-TREATMENT CONDITION ON PAVEMENT MANAGEMENT DECISIONS

6.1 Introduction of Monte Carlo Simulation

Uncertainty, ambiguity, and variability exist in every pavement management decisions. To account for these factors, risk analysis allows combining probabilistic descriptions of uncertain input parameters with computer simulation technique in quantitative analysis and decision-making. In this respect, simulation is virtually a rigorous and extended sensitivity analysis. It uses input values randomly drawn from the input probability distributions to get output that can be presented in the form of a probability distribution; which allows for describing the range of possible outcomes along with a probability of occurrence.

Monte Carlo simulation is the most common computerized mathematical simulation technique allowing for modeling decision making under uncertainty. Monte Carlo simulation is most useful when obtaining a closed-form expression is difficult or applying a deterministic algorithm is infeasible. By using this method, the decision maker knows both the full range of possible values, and the relative probability of any particular outcome actually occurring. This is exactly the information that the decision maker needs in order to make an erudite decision.

The number of iterations that Monte Carlo simulation runs can be in the thousands, even tens of thousands, depending on the number of uncertainties and the ranges specified for them. Monte Carlo simulation produces distributions of possible outcome values. In other words, each iteration represents a possible scenario or outcome, the results of which are captured, complied and subjected to statistical analysis. This process of sampling from a probability distribution is repeated until the specified number of iterations is completed or until the simulation process converges. To ensure low probability values have sufficient opportunity to be sampled, the Monte Carlo simulation typically requires a large number of iterations, especially when highly skewed distributions are used to describe the input variables.

6.2 Monte Carlo Simulation of M&R Need Estimates

In this study, Monte Carlo simulation is used to capture the effect of uncertainty in unit cost and pre-treatment condition of M&R projects on need estimates (i.e., needed funding). This simulation process is illustrated in Figure 6.1 and Figure 6.2. Figure 6.1 represents the simulation process for each individual project (i.e., estimated cost for each M&R project). Figure 6.2 represents the simulation process for all projects combined (i.e., estimated total funding needed for the network).

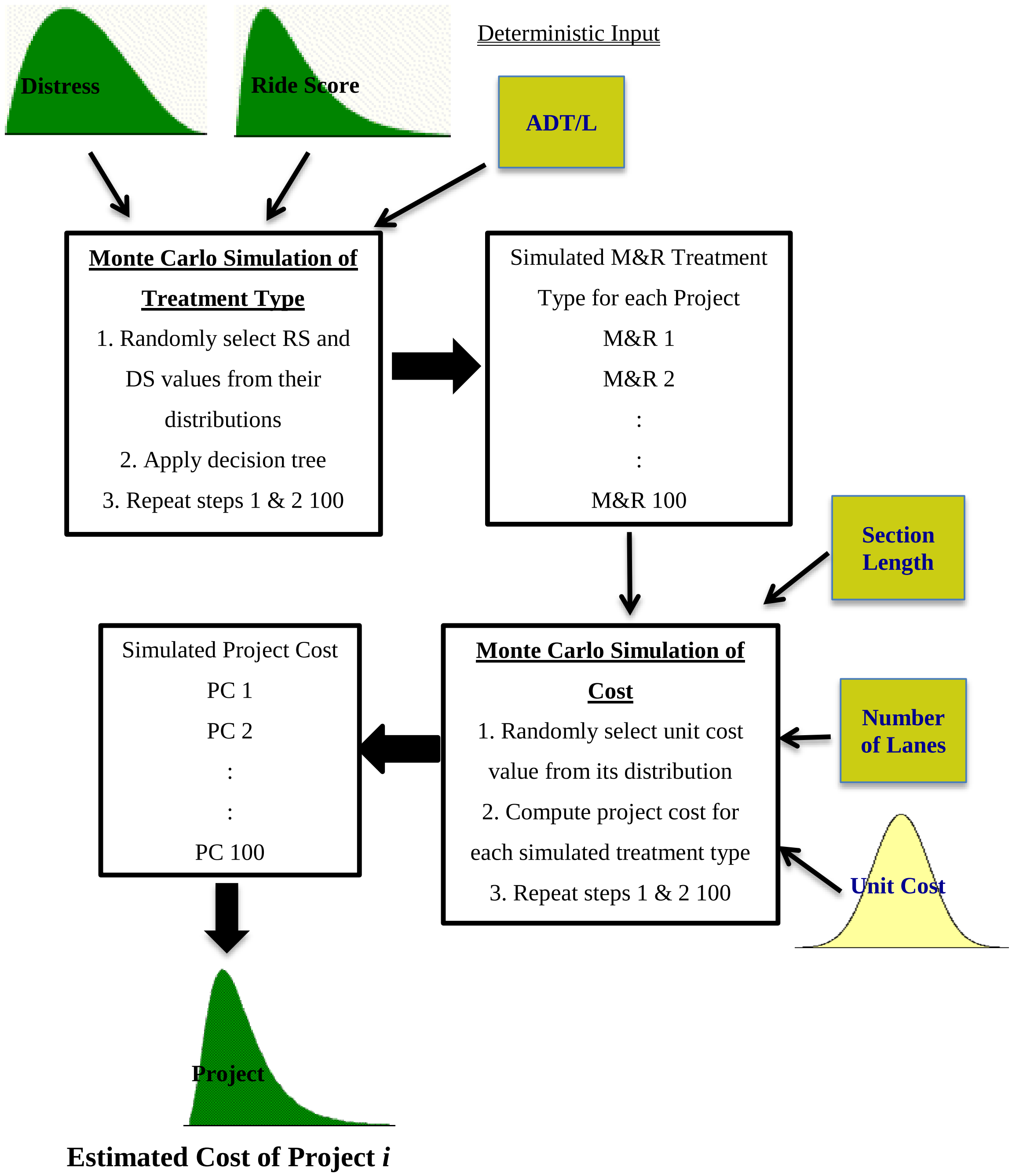


Figure 6.1 Monte Carlo Simulation of the Cost of each M&R Project

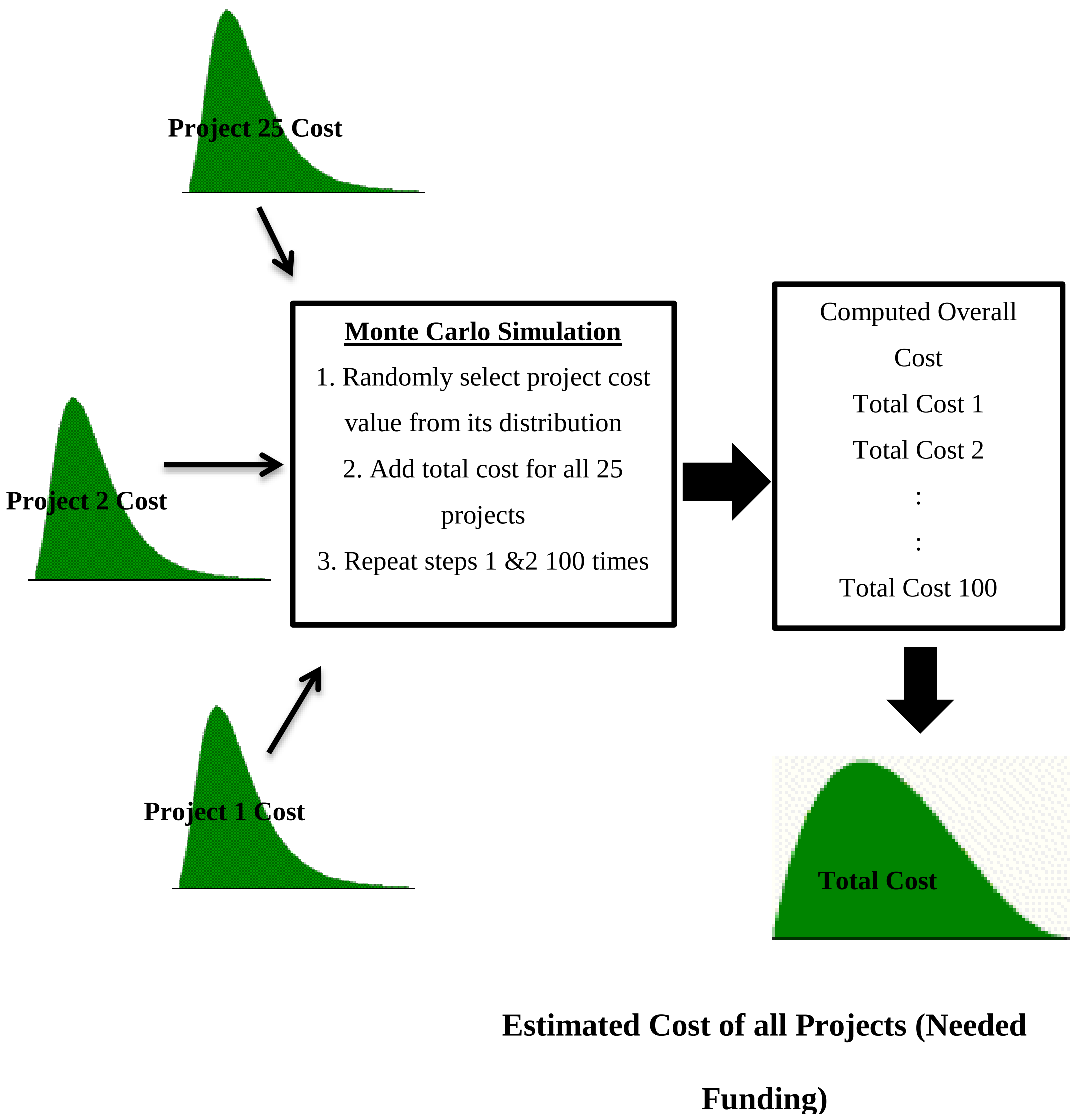


Figure 6.2 Monte Carlo Simulation of Total Cost of All 25 Projects Combined (Needed Funding)

In this process, distress score, ride score, and unit cost were treated as probabilistic inputs; whereas ADT/L, section length, and number of lanes are treated as deterministic inputs. As discussed before, 25 out of 29 projects, the M&R treatment types of which are determined by simplified decision tree and listed in PMPs are comparable. These 25 projects are used in this research to measure the uncertainty. The probability distributions of distress scores and ride scores for these 25 projects and the probability distributions of unit cost were discussed earlier in Chapter 4.

By performing the Monte Carlo simulation, a hundred samples are randomly drawn from each input distribution to represent a what-if scenario (i.e., iteration). M&R treatment recommendations were obtained from the decision tree in the form of a discrete probability distribution that describes the probability of occurrence. The reason that the M&R treatment recommendations are represented by a discrete distribution is the treatment type can only be PM or Rehab.

After obtaining the M&R treatment type distribution for each project, the project cost can be calculated by:

$$\text{Pr}\,oject\,Cost = Number\,of\;\;Lanes\;\times Section\,Length \times Unit\,Cost$$

The process is repeated for all 25 projects and the overall estimated cost for all projects combined is computed as follows:

$$Overall\,Cost = \text{Pr}\,oject\,1\,Cost + \text{Pr}\,oject\,2\,Cost + \cdots \text{Pr}\,oject\,25\,Cost$$

The probability distribution of the overall cost (obtained from Monte Carlo simulation) is shown in Figure 6.3. The total cost for these 25 projects obtained from the district’s PMP (see Table 6.1) is 17.5 million dollars. Based on overall cost distribution obtained from Monte Carlo simulation, the 90% prediction interval for overall cost is between 9 million dollars to 19 million dollars. Thus, the overall cost of the 25 projects listed in PMPs falls within the 90% prediction interval determined in this analysis.

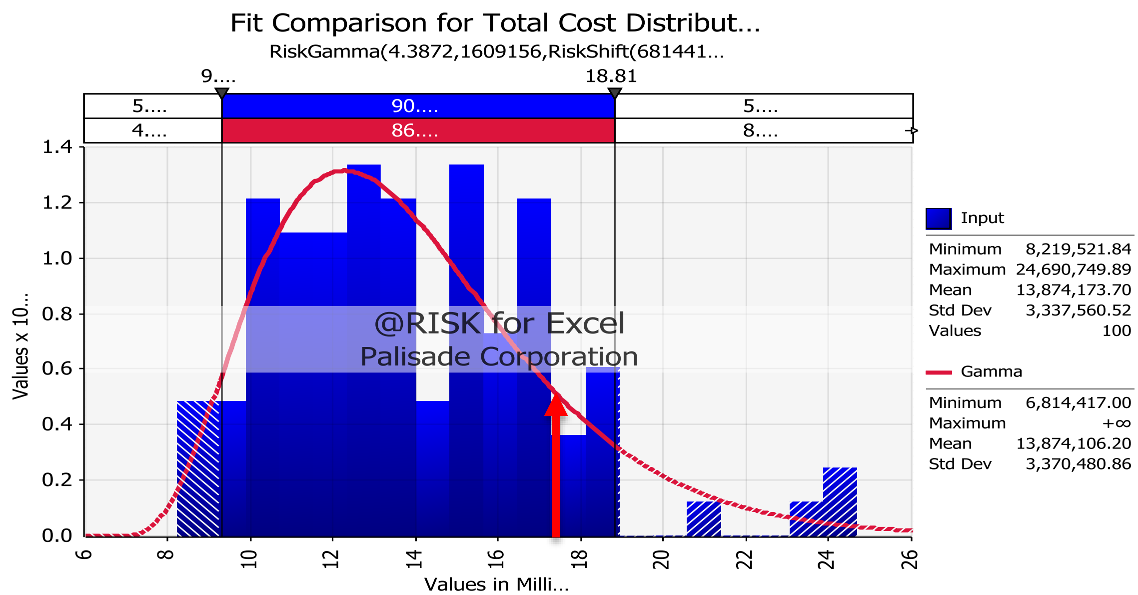


Figure 6.3 The Overall Cost Distribution of All Projects (Need Estimates)

Table 6.1 Project Costs Estimated by the Bryan District

Project No.	County No.	Highway ID	BRMN	BRMN Disp	ERMN	ERMN Disp	At Completion Expense Cost	M&R Type
1	21	SH0006 A,X	674	1.811	676	1.101	$330,894	PM
2	26	SH0036 k	552	0.432	556	0.507	$386,672	PM
3	26	SH0036 K,L,R	556	0.507	558	0.637	$197,951	PM
4	198	US0079 K,L,R	480	1.522	490	0.403	$308,149	PM
5	198	US0079 K	462	1.706	470	1.868	$307,047	PM
6	198	US0079 K	478	1.171	480	1.5222	$112,880	PM
7	145	US0079 K	458	0.002	462	1.705	$206,568	PM
8	145	US0079 K	438	1.662	446	1.69	$336,773	PM
9	145	US0079 K	422	1.623	438	0.446	$599,956	PM
10	166	US0077 K,L,R	426	2.061	432	1.444	$213,052	PM
11	166	US0077 K	432	1.444	438	1.896	$227,079	PM
12	166	US0077 K	438	1.896	448	0.958	$336,832	PM
13	236	US0190 K	752	1.017	754	1.775	$856,975	PM
14	239	FM0050 K	438	0.921	452	0.002	$482,230	PM
15	154	SHOSR K	632	0.835	648	1.489	$585,275	PM
16	154	SHOSR K	654	1.492	666	1.271	$445,841	PM
17	154	FM0039 K	404	1.797	412	0	$228,393	PM
18	82	IH0045 R	198	0.047	205	0.473	$2,714,778	PM
19	82	IH0045 L	198	0.047	204	0.448	$2,425,509	PM
20	94	FM1696 K	642	-0.03	650	1.139	$357,143	PM
21	166	FM2095 K	582	0.703	594	1.921	$552,140	PM
22	236	FM2693 K	672	-0.65	676	0	$188,341	PM
23	21	FM2818 K	406	-0.04	410	0.615	$873,959	PM
24	26	SH0021 K	620	0	622	0	$374,001	MR
25	21	FM1179 K	412	0.461	414	0.029	$3,877,240	MR
		Overall Cost Estimated by District					**$17,525,678**	

7. SUMMARY AND CONCLUSION

A novel probabilistic methodology for estimating M&R funding needs for pavement networks was developed and applied to a sample roadway network. This methodology explicitly accounts for uncertainties observed in pavement pre-treatment condition and unit cost for each maintenance and rehabilitation treatments was developed. This approach for estimating M&R funding needs provides a justifiable manner that allows highway agencies to develop more realistic estimates of needed funding.

Data was obtained from the Bryan district pavement management plan for 2012 and from the Texas Department of Transportation Pavement Management Information System. Probability distribution functions were fitted for distress score, ride score, and unit cost. Also, a simplified decision tree was developed to help simulate the maintenance and rehabilitation treatment selection process. This decision tree considers ride score, distress score, and traffic volume.

Based on the results of this research, the following conclusions can be made:

- The probability distribution types for distress score and ride score appear to vary among projects. However, triangular distribution was most common for distress score and pert distribution was most common for ride score.
- Preventive maintenance unit cost was found to follow loglogistic probability distribution.
- Rehabilitation unit cost was found to follow pert probability distribution.

- The M&R treatment types determined by simplified decision tree and those listed in Bryan District PMP for 2012 agreed 86.2 percent of the time (25 out of the 29 projects have the same M&R treatment type).
- The district's PMP estimated the overall cost of all 25 projects to be 17.5 million dollars; whereas the Monte Carlo simulation process estimated this cost to range from 9 million dollars to 19 million dollars. Thus, the overall cost of the 25 projects listed in PMPs falls within the 90% prediction interval.

In conclusion, these results stress the capacity of the stochastic method to improve pavement management decision by considering the uncertainty in pavement condition measurements and unit cost of maintenance and rehabilitation treatment type.

8. RECOMMENDATIONS

Recommendations for future work include:

- Investigate the probabilistic nature of other inputs to the need estimation process (e.g., ADT).
- Consider additional M&R projects in the fitting of probability distributions.
- Use more specific M&R treatment types. The M&R types used in this study were constrained to PM and Rehab due to the limited data.
- Extend the simplified decision tree to consider additional factors and pavement types.
- Validate the developed methodology using data from other roadway networks (e.g., other TxDOT districts).

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APPENDIX A

Table A.1 M&R Projects Used in Decision Tree and Simulation Process (Fiscal Year 2012)

Project No.	County Number	Highway System	Highway No.	Roadbed ID	BRMN	BRMN Disp	ERMN	ERMN Disp	Length	Pavement Type	M&R Treatment
1	21	SH	6	A, X	674	1.811	676	1.101	1.29	ACP	PM
2	26	SH	36	K	552	0.432	556	0.507	4.075	ACP	PM
3	26	SH	36	K, L, R	556	0.507	558	0.637	2.13	ACP	PM
4	198	US	79	K, L, R	480	1.522	490	0.403	8.881	ACP	PM
5	198	US	79	K	462	1.706	470	1.868	8.162	ACP	PM
6	198	US	79	K	478	1.171	480	1.5222	2.351	ACP	PM
7	145	US	79	K	458	0.002	462	1.705	5.703	ACP	PM
8	145	US	79	K	438	1.662	446	1.69	8.028	ACP	PM
9	145	US	79	K	422	1.623	438	0.446	14.823	ACP	PM
10	166	US	77	K, L, R	426	2.061	432	1.444	5.683	ACP	PM
11	166	US	77	K	432	1.444	438	1.896	6.452	ACP	PM
12	166	US	77	K	438	1.896	448	0.958	9.062	ACP	PM
13	236	US	190	K	752	1.017	754	1.775	2.758	ACP	PM
14	239	FM	50	K	438	0.921	452	0.002	11.981	ACP	PM
15	154	SH	OSR	K	632	0.835	648	1.489	16.654	ACP	PM
16	154	SH	OSR	K	654	1.492	666	1.271	11.779	ACP	PM
17	154	FM	39	K	404	1.797	412	0	6.203	ACP	PM
18	82	IH	45	R	198	0.047	205	0.473	7.426	ACP	PM

Table A.1 Continued

Project No.	County Number	Highway System	Highway No.	Roadbed ID	BRMN	BRMN Disp	ERMN	ERMN Disp	Length	Pavement Type	M&R Treatment
19	82	IH	45	L	198	0.047	204	0.448	6.401	ACP	PM
20	94	FM	1696	K	642	-0.03	650	1.139	9.069	ACP	PM
21	166	FM	2095	K	582	0.703	594	1.921	13.218	ACP	PM
22	236	FM	2693	K	672	-0.65	676	0	4.651	ACP	PM
23	21	FM	2818	K	406	-0.04	410	0.615	4.658	ACP	PM
24*	198	FM	391	K	396	-0.98	398	0.078	3.057	ACP	PM
25*	82	FM	488	K	322	0.995	320	-1.91	4.907	ACP	PM
26*	198	FM	1940	K	618	1.067	628	0.05	8.783	ACP	PM
27*	236	PR	40	K	412	-1.92	412	-0.51	1.409	ACP	PM
28	26	SH	21	K	620	0	622	0	2	ACP	MR
29	21	FM	1179	K	412	0.461	414	0.029	1.568	ACP	MR

* Indicates project used in development of simplified decision tress, but was not used in the simulation process because the treatment type determined by the decision tree for these projects did not match that listed in the PMP.